Crisis Determination and Financial Contagion: An Analysis of the Hong Kong and Tokyo Stock Markets using an MSBVAR Approach

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Abstract

International financial crises have often been blamed on the phenomena of 'financial contagion.' However, despite extensive research over the past two decades, the existence of financial contagion has been widely contested with many economists failing to agree upon appropriate methods for time-series selection and correlation modelling.

Although much research appears to have been conducted into the existence of contagion during financial crises of the 1990's, there is seemingly less analysis of the subject using recent financial data.

Using multi-frequency stock market data from the Hang Seng and Nikkei 225 Indices over the period 2004-2014, this paper analyses correlations between the Hong Kong and Tokyo stock markets over different subsamples, adding to the lasting debate of financial contagion. Employing Pearson and Spearman correlation measures, the dynamic relationship of these two markets is determined over tranquil and crisis periods, as specified by an MSBVAR model.

We find evidence in support of the existence of financial contagion (defined as an increase in correlation during a crisis period) for all frequencies of data analysed. This contagion is greatest when examining lower-frequency data. Additionally, there is also weaker evidence in some data subsamples to support 'herding' behaviour, whereby higher market correlations persist, following a crisis period.

Key words / phrases: financial contagion; correlation; MSBVAR.

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1. Introduction

The 1990's saw many emerging economies significantly affected by economic crises. Following the burst of Japan's economic and financial bubble in 1989, currency crises in Europe and Mexico led to stock market declines in a number of European and Latin American economies. In 1997 the forced devaluation of the Thai Baht and rumours that Hong Kong would too abandon its fixed rate system prompted a string of stock market declines in neighbouring East Asian economies. In 1998 a devaluation of the Russian Rouble, simultaneous with Russia's default on its treasury debt caused shockwaves to bond and stock markets around the world. Brazil, Ecuador and Argentina all suffered currency depreciations or credit defaults between 1999 and 2001.

This fascinating and eventful period in economic history led to a significant amount of research surrounding correlation and causality within financial markets. The term 'financial contagion' has been coined by various economists to describe this phenomenon but despite more than two decades' of research, there is still no consensus on exactly what that term means.

Use of the term 'contagion' is long-established in economics, for example, being used to refer to the spread of strikes across firms (Price 1890) and the spread of wage growth championed by unions to non-union firms (Ulman 1955). In the current context, most definitions of financial contagion refer to the "spread of financial turmoil across countries" (Claessens and Forbes 2001: 2), although it is often argued that only very specific transmission mechanisms such as irrational investor behaviour amount to contagion (Caporale et al 2005).

The World Bank defines contagion as "the cross-country transmission of shocks or the general cross-country spillover effects" (World Bank 2013). Additionally, it also uses a 'restrictive' definition, which employs the same terminology but strictly *after* controlling for the effects of macroeconomic fundamentals. This definition has been used widely, particularly by Eichengreen and Rose (1995) and Eichengreen, Rose and Wyplosz (1996).

Perhaps the most frequently used definition of contagion however, (and also the one adopted by this paper) comes from Forbes and Rigobon (2002: 2223), who define contagion to mean "a significant increase in cross market linkages after a shock to one country (or a group of countries)." This definition therefore excludes the case where markets display a large degree of comovement during both stable and crisis periods and allows for comment on international diversification, and the evaluation of the effectiveness of international organisations in controlling economies (Billio and Caporin 2010).[3]

It should also be noted that, in addition to the debate on the definition of contagion, some economists contest its existence at all (Karolyi 2003). Many economists reason that what might appear to be contagion, can often actually be attributed to some other factor such as mean spill-over effects. This debate will be briefly outlined during Section 2, but as stated, this paper will use the definition provided by Forbes and Rigobon and therefore will not venture deeply into identification and analysis of causal factors for any financial contagion that might be present.

Finally, many researchers also discuss the existence of herding behaviour, categorised as continued high market correlations following a crisis period (Chiang, Jeon and Li 2007).

[3] A full summary of types of contagion can be found in Naoui, Liouane and Brahim (2010).

Gentile and Giordano (2012) describe herding as a reason for spillover effects between countries, suggesting that the behaviour arises from imperfect information among investors. In this instance, if information for less-refined investors is costly, they tend to follow the actions of other (supposedly well-informed) investors, anticipating that their actions echo future price changes. Often both during and after periods of financial crisis, increased market correlations can be observed resulting from this mimicking behaviour.

The purpose of this paper then, is to add to the existing literature on financial contagion. While a vast amount of the debate has been made using data from the late 1990's, this paper differentiates itself by analysing more current data, centred around the most recent global financial crisis, with specific focus on the stock markets of Hong Kong and Tokyo. Additionally, the existing research is greatly diversified in terms of both the econometric techniques employed (particularly in determining periods of financial crisis) and the frequency of data analysed. This paper examines a multitude of data frequencies to determine the significance of accurate data selection on the observation of financial contagion. This paper therefore aims to answer three questions. Firstly, is there sufficient evidence to support the existence of financial contagion between the stock markets of Hong Kong and Tokyo, during the period of 2004-2014? Secondly, if the evidence supports the existence of contagion, does this contagion persist following a crisis period (i.e. is there evidence of herding behaviour), or are the effects reduced over time? Thirdly, does the frequency of the time series analysed have an impact on the observed results.

The research finds that correlations between the stock markets of Hong Kong and Tokyo are markedly higher during times of crisis than times of tranquillity. This is taken as evidence of financial contagion, under the definition advocated by Forbes and Rigobon (2002). Additionally, there is some evidence to support herding behaviour following a financial crisis, although this does not occur in every period, and should be interpreted with caution, particularly when subsample sizes are small. Finally, the paper finds that increases in correlation over tranquil and crisis periods are largest when examining lower-frequency data.

The analysis conducted by this paper has relevance to financial issues relating to optimal responses of portfolio managers during times of economic distress. Additionally, the results provide general support for the intervention of world bodies such as the International Monetary Fund (IMF) intended to halt the spread of financial crisis between countries and regions.

The remainder of this paper is structured as follows. Section 2 provides a comprehensive literature review targeted at research into financial contagion. Section 3 offers description of the data and statistics of stock returns for the Hang Seng and Nikkei 225 Indices. Section 4 outlines the methodology employed to examine the data, with justifications for selection of the models employed. Section 5 provides the results of regression analysis, together with their interpretation and Section 6 concludes.

2. Literature Review

Throughout the 1990's, many emerging market economies were dominated by economic crises, originating as country specific events and quickly spreading to other countries around the globe. The occurrence of crises in Latin America (1994), Asia (1997) and Russia (1998) sparked a swathe of research into the topic of correlation and causality within financial markets, leading many economists to coin the term 'contagion' to describe this phenomena.[4]

Literature into the topic differs greatly in terms of choice of markets, countries and time periods, but also by the choice of modelling techniques used and their interpretation. The aim of this section is to provide a brief but comprehensive synopsis of past and current literature that closely relates to the study of this paper, outlining their objectives and methodologies, reasoning why the outcomes of various studies differ or conflict. This section provides much of the justification for the methodology used in this paper, which will be further outlined in Section 4.

Two main issues have been faced by past researchers. Firstly, much research has been constructed around the importance of accuracy in determining the timing and duration of crisis periods affecting financial markets. Secondly, there has been significant debate by researchers attempting to determine the best way to analyse correlation dynamics before, during and after these crisis phases.

The problem of accurately determining a crisis period is evident in the variation of results that are achieved. Baig and Goldfajn (1999), Forbes and Rigobon (2002), Boyer et al (2006) and Rodriguez (2007) all model different crisis periods to analyse contagion during the Asian financial crisis of 1997 and they all conclude different results. Generally, the literature has taken one of two approaches, determining crisis periods either exogenously or endogenously. Exogenous determination is often events-based (Dungey et al (2002), Forbes and Rigobon (2002)) but many researchers have also identified crisis periods through the presence of heteroskedasticity (for example Eichengreen, Rose and Wyplosz (1995)), identifying higher observations of volatility, which can occur during crisis periods. Dungey (2003) argues that this approach surmounts to sample selection bias as the volatility threshold still remains an exogenous factor.

Commonly, studies which examine market correlations inside and outside crisis periods suffer from uneven sampling periods. The crisis period is usually much shorter than the non-crisis period which Inci et al (2010) argue can undermine the power of tests for changes in the underlying time series' probability distribution. Baur (2012) notes that the length of crisis periods, when determined endogenously, far exceed those determined using exogenous methods.

In order to reduce issues associated with selection bias, many researchers have then adopted endogenous approaches to determine crisis periods. Baur and Fry (2009) use panel data comprising daily price data from various Asian stock markets. The authors argue that by assessing contagion on a daily basis, the results can be extended to a multiple of the actual length of the crisis period and are therefore not constrained as features of the sample period. Baur and Fry claim this endogenous approach removes sample selection bias.

[4] Aptly, these crises have now been termed the 1994 'Tequila Effect,' the 1997 'Asian Flu' and the 1998 'Russian Cold.'

Some more recent literature has adopted the techniques of Markov switching (MS) models, which calculate probabilities of states within time series data, based on presupposed restrictions on the total number of unique periods. Rodriguez (2007) uses a MS regime model to endogenously identify a crisis period of several months, compared to a period of just 20 trading days analysed by Forbes and Rigobon (2002), who use an events-based approach.[5]

Finally, Baur (2012) uses a combination of both exogenous and endogenous methods to determine the length of the crisis period, arguing that this approach allows flexibility through the incorporation of economic and financial events, whilst maintaining the econometric rigour not achievable with an ad-hoc exogenous approach. Further details on the sampling properties of contagion testing are given in a comprehensive account by Dungey et al (2005).

This paper will use MS techniques similar to those of Rodriguez (2007), which are employed to resolve the issues described above. Further details of the exact methodology used in this paper can be found in Section 4.

In addition to the debate on the most appropriate method of determination of crisis periods, there has been much literary discussion as to the most effective or statistically rigorous method of modelling contagion itself. Often, economists reason that the use of different methodologies can explain the variations of results of studies into the existence of financial contagion (Serwa and Bohl (2005), (Paas and Kuusk (2012)).

Econometric models used in the analysis of contagion have been developed from traditional models of interdependence of asset markets during non-crisis periods. These latent factor models are based upon Arbitrage Pricing Theory (APT) where the determination of asset returns comes from both common and idiosyncratic factors, representing both diversifiable and non-diversifiable risk. Models of interdependence have then monitored the covariance between asset returns, resulting solely from these common factors (Dungey et al 2003).

A number of studies then conduct bivariate and multivariate tests for contagion. Dungey and Martin (2002) perform a bivariate test analysing pairs of asset returns for volatility changes. First, they compute the covariance between asset returns of two countries during the crisis period as:

$$E[y_{1t}, y_{2t}] = \lambda_1\lambda_2 + \gamma\delta_1$$

Secondly, this value is compared with the calculated covariance during the pre-crisis period:

$$E[y_{1t}, y_{2t}] - E[x_{1t}, x_{2t}] = \gamma\delta_1$$

A simple test can be performed on γ to determine if an increase or decrease in covariance occurred during the crisis period.

Many studies then, ascertain the existence of contagion by comparing the Pearson correlation coefficient between markets during times of stability and crisis (Hon, Strauss and Yong (2004), Li (2009)). The intention of this paper is to adopt a similar methodology but there are a number of problems associated with this approach, which need to be overcome.

Traditional correlation analysis has assumed that financial returns exhibit a Gaussian normal distribution but it is now widely documented that the variance of aggregate stock returns is generally not constant over time (Fama (1963), French, Schwert and Stambaugh (1987)).

[5] Both papers use data from the Latin American and Asian crises of the 1990s.

Forbes and Rigobon (2001) conclude that the presence of heteroskedastic error terms will create bias in the test for contagion.

Factor models can be easily extended to include lagged variables of asset returns. One of the simplest and most common methods is use of a Vector Auto-Regression (VAR) model. For example, Baig and Goldfajn (1999) employ VAR techniques to determine impulse responses to shocks in the equity and currency markets of Thailand, Malaysia, Indonesia, Korea and the Philippines between 1995 and 1998. They find evidence of cross-border contagion in both the stock and currency markets, proving that these Asian markets had behaved significantly differently than a control group of European markets that were not experiencing financial crises during the time period analysed.

Another oft-cited study is that of Khalid and Kawai (2003) who employ a multivariate VAR model to analyse contagion between Asian markets during the 1997/98 economic crisis. Modelling each endogenous variable as a function of the lagged values of all endogenous variables, the authors measure correlation responses to various impulse shocks but find only short-lived contagion, which disperses quickly. In their analysis, Khalid and Kawai use the AIC, SIC and LR to determine the optimal lag-length for VAR modelling.[6]

Forbes and Rigobon (2002) also attempt the use of a VAR methodology to filter out common shocks in their models of the 1997 Asian crisis, the 1994 Mexican devaluation and the 1987 US market crash. Although they find evidence of a 'high level of market comovement in all periods,' Forbes and Rigobon classify this as a result of interdependence rather than contagion. The methodology used in our research involves combining the MS techniques used by Rodriguez (2007) with the VAR methodologies of Baig and Goldfajn (1999) and Forbes and Rigobon (2002), enabling more accurate modelling of the crisis period, based on lagged values of each stock market. This MSVAR approach has previously been implemented successfully by Brandt and Freeman (2012) who use the technique to determine crisis periods within datasets relating to the violent conflict between Israel and Palestine. In the literature on financial contagion, Zhou et al (2014) construct MSVAR models to measure the nonlinear correlation between stock returns in Shanghai, Hong Kong and America, finding differing characteristics in the correlations among markets and various dynamic causal relationships. The MSVAR approach adopted in this paper then, also takes inspiration from the work of Zhou et al (2014).

Additionally, a substantial amount of contagion analysis has been conducted using Generalised Auto-Regressive Conditional Heteroskedasticity (GARCH) models, following the seminal work of Bollerslev (1990) who examined nominal European-US Dollar exchange rates following adoption of the European Monetary System (EMS) in 1979. As mentioned, many financial datasets exhibit heteroskedasticity, causing the standard errors and confidence intervals estimated by an OLS regression to be too narrow, leading to an inaccurate sense of precision (Engle 2001). ARCH / GARCH methods model heteroskedasticity of the error terms to correct for deficiencies of the more traditional OLS methods.[7] Using the GARCH method, Bollerslev found co-movements between currencies to be significantly higher when compared to the period before the EMS free float.

[6] Akaike Information Criteria, Schwartz Information Criteria and the Likelihood Ratio are all commonly used to determine lag length for VAR models. The objective is to select a lag-length just long enough that the residuals are white noise, whilst maintaining the precision of the estimates (Canova 2007).

[7] ARCH models only use the most recent squared residuals to estimate the fluctuating variance. The GARCH model relaxes this restriction by adopting a long memory process, including all past squared residuals to estimate current variance.

Saleem (2008) notes that multivariate GARCH approaches are preferred (over univariate models) but the restriction of positive definiteness that is imposed on the conditional variance-covariance matrix is often restrictive. Billio and Caporin (2010) comment that basic multivariate GARCH models suffer a number of problems in the context of financial contagion analysis. In particular, Francq and ZakoÏan (2004) note that the asymptotic properties of the Quasi Maximum Likelihood Estimation (QMLE) are commonly violated when GARCH models are applied to financial data. Full details will not be discussed here, but further information can be found in Zivot (2008) and Conrad and Mammem (2015).

Then, due to the complexities associated with use of the GARCH model in the context of financial contagion, the analysis in this paper instead uses logarithms and first differences of stock market data to reduce the persistence of heteroskedasticity. By implementing the MS model as a way of determining multiple structural breaks within the data and analysing correlations separately during each period, this paper attempts to eradicate the existence of heteroskedasticity, without introducing unnecessarily complex analysis through implementation of GARCH techniques. Further details of these procedures will be discussed in Sections 3 and 4.

Despite a number of positive studies, the existence of contagion has been strongly contested. Karolyi (2003) argues that there is weak evidence of contagion and that lack of consensus on its definition means it is difficult to determine its existence at all. Favero and Giavazzi (2002) choose to avoid using the term 'contagion' entirely in their study of non-linearity of international propagation of financial shocks. Moser (2003) contests that a significant proportion of 'contagion' is simply 'shock propagation through fundamentals' and so we should distinguish between 'pure contagion' and what is simply 'transmission.' But a lack of evidence of contagion in some studies can simply indicate that it perhaps does not occur within the analysed economy or time period, rather than that it does not exist entirely.

A number of authors then, have conducted studies that show no evidence of contagion. The single-lag VAR models constructed by Khalid and Kawai (2003) to determine the existence of contagion among stock, money and currency markets across nine East Asian economies fail to provide significant evidence to support the existence of contagion among any of the data sets analysed. This result is confirmed by employing a modified Wald procedure[8] to test Granger causality, where again the results fail to point toward strong contagion within Asian markets.

Dungey et al (2002) note that data frequency can impact the results of contagion analysis. Many studies choose frequency largely based upon the availability of macroeconomic and financial data. The use of various fundamental data can significantly lower the frequency employed, impacting results of economic and econometric analysis into the existence or persistence of financial contagion (Moser 2003). In this paper, econometric models are constructed for multiple data frequencies ranging from daily to quarterly observations, in order to determine the impact of data frequency selection on the observation of financial contagion.

Despite the vast literature surrounding crises in the 1990's, there has as yet been substantially less coverage of the most recent financial crisis in the context of financial contagion. One possible reason for this can be found in Dungey and Tambakis (2003), who

[8] Toda and Yamamoto (1995) developed a Wald test statistic which asymptotically has a X^2 distribution irrespective of the order of integration or cointegration properties exhibited by the variables in the model. The test is relatively simple to perform and is widely used to test for causality between integrated variables (Hacker and Hatemi-J: 2003).

note that extensive evidence points towards an increasing correlation between international financial markets. This view is supported more recently by Lewis (2006) and Fenn et al (2011). Notably Chi et al (2006) comment that integration of East Asian equity markets has increased over time, while Jeon et al (2006) observe similar findings, reasoning that this increased regional integration is a result of East Asian markets becoming more globally integrated.[9] Given the general increase in market correlations, it might be logical to suppose that financial contagion is no longer a prevailing factor. However, by analysing market correlations before, during and after crisis periods, often across relatively short subsamples, this time trend is not anticipated to be a prevailing factor. It is therefore sensible to conclude that analysis of financial contagion during the most recent financial crisis represents important empirical work.

As mentioned, this paper will employ an MSBVAR methodology largely developed by Brandt and Freeman (2012) and in line with the approach taken by Rodriguez (2007) and Zhou et al (2014). This paper adds to the existing literature on financial contagion by examining market correlations over varying frequencies of stock market data. This methodology will be explained in further detail in Section 4.

3. Data

This section introduces the data which is to be used for econometric estimation and empirical analysis. We provide basic analysis and summary statistics, which will form the basis of the methodology constructed in the following section of this paper.

This paper uses time-series stock market data from Hong Kong's Hang Seng Index (HSI) and Tokyo's Nikkei 225 Index (NSI) in five frequencies ranging from daily to quarterly observations. The data used is measured in local currency and obtained from Yahoo! Finance. The sample consists of (at most) 2870 observations, spanning 01-01-2004 to 31-12-2014. This time period is considered an ideal length to capture an accurate representation of market correlations before the anticipated crisis period. As mentioned, Dungey and Tambakis (2003) note a trend of increasing correlation between international financial markets, so if the period analysed in this paper were longer, the recorded level of correlation during the pre-crisis period might be spuriously low. In this research, data from the Nikkei 225 index is used as a proxy for the Tokyo stock market although alternative literature has also used the Tokyo Stock Price Index (TOPIX) in a similar manner.

Where time series data are unavailable, or not applicable, we assume that the market takes the closing price from the previous period. This issue is not present among lower frequency data but for daily data, this procedure is necessary to ensure data sets of equal length for both time series'.[10] This is a widely accepted solution to this minor complexity (Tan 1998).

Figure 1 shows the daily closing prices of HSI and NSI over time. The data clearly show peaks in values of both markets in 2007, with subsequent decreases throughout 2008, roughly the time of the global financial crisis. Initial analysis appears to show some degree of

[9] Although some studies disagree with this position (Bekaert et al (2009), Asness, Israelov and Liew (2010)), the majority of studies seem to indicate a general increase in international financial market correlation over time.

[10] For example, Japan and Hong Kong do not share the same public holidays and so there are a number of instances where one market is stock open and the other is closed. Assuming that the closed market simply returns a value equal to its previous observation negates this issue.

comovement between the two indices and we consider summary statistics of the data to determine this further. For brevity, we show only the summary statistics of the daily price data in this section. Full summary statistics of all frequencies can be found in Appendix 1.1. Statistics for the daily time series are presented in Figure 2.

Figure 1: HSI and NSI over Time

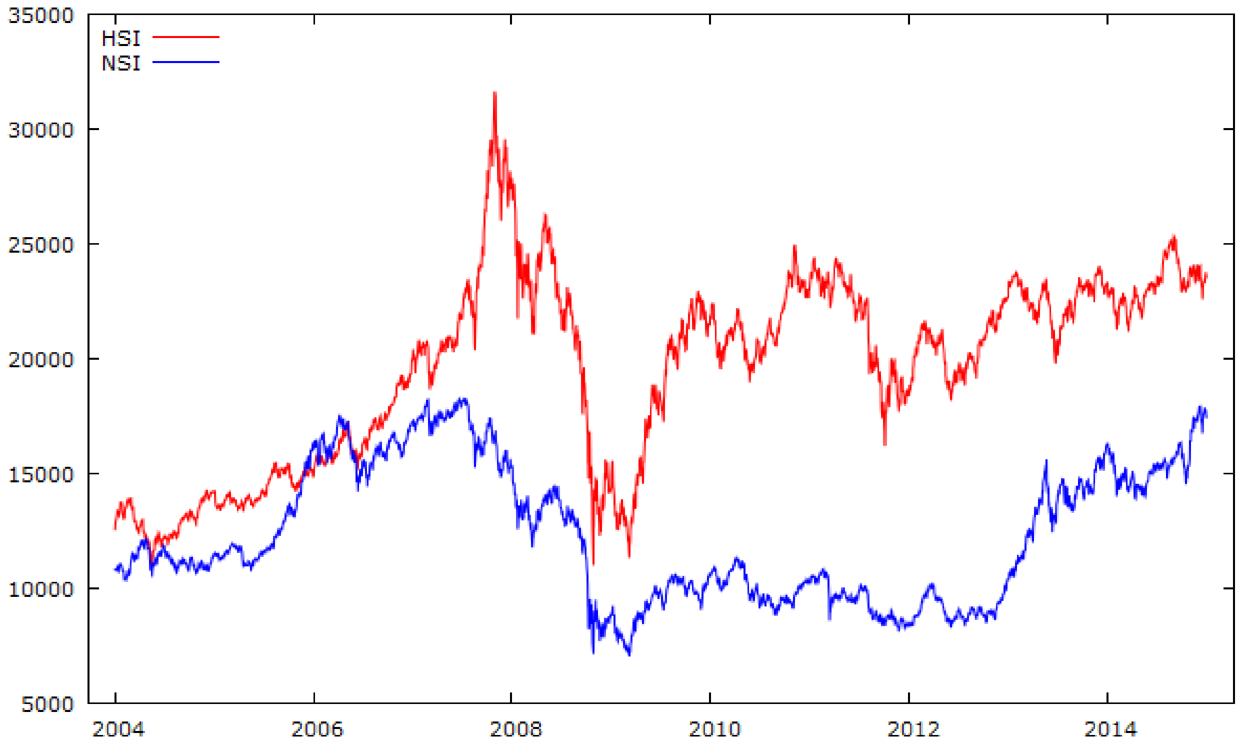


Figure 2: Summary Statistics, using the observations 01-01-2004: 31-12-2014

Variable	Mean	Median	Minimum	Maximum
HSI	19587	20592	10968	31638
NSI	12345	11496	7055	18262
Variable	**Std. Dev.**	**C.V.**	**Skewness**	**Ex. kurtosis**
HSI	4049.8	0.20676	-0.25741	-0.75535
NSI	2938.9	0.23807	0.32854	-1.2013
Variable	**5%**	**95%**	**IQ range**	**Missing obs.**
HSI	12836	24703	6978.9	0
NSI	8542.4	17355	5316.8	0

We note that across the period, the values of both the HSI and NSI have fluctuated to similar extremes with their maximum values each being around 2.5 times their minimums. Both series are skewed away from the normal distribution to similar degrees in absolute terms, with the HSI exhibiting a negative skew of 0.2574 and the NSI displaying a positive skew of 0.3285. The Jarque-Bera statistics confirm that we reject the null hypothesis of normal distribution[11] and the negative excess kurtosis values indicate distributions flatter than the normal distribution.[12] This platykurtic distribution is expected, based on the graphed

[11] Jarque-Bera statistics are measured against critical values of the X^2 distribution with two degrees of freedom (one for skewness and the other for kurtosis). Values are 99.924 for HSI and 224.212 for NSI. Therefore we reject the null hypothesis of normality at the 1% level in both cases. A complete summary of JB statistics for the models estimated can be found in Appendix 1.3.

[12] Kurtosis for the normal distribution is 3, so excess kurtosis refers to cases when kurtosis ≠ 3. Commonly, stock market returns are found to be leptokurtic (i.e. they exhibit kurtosis > 3), but this is not always the case and can vary with the time period analysed.

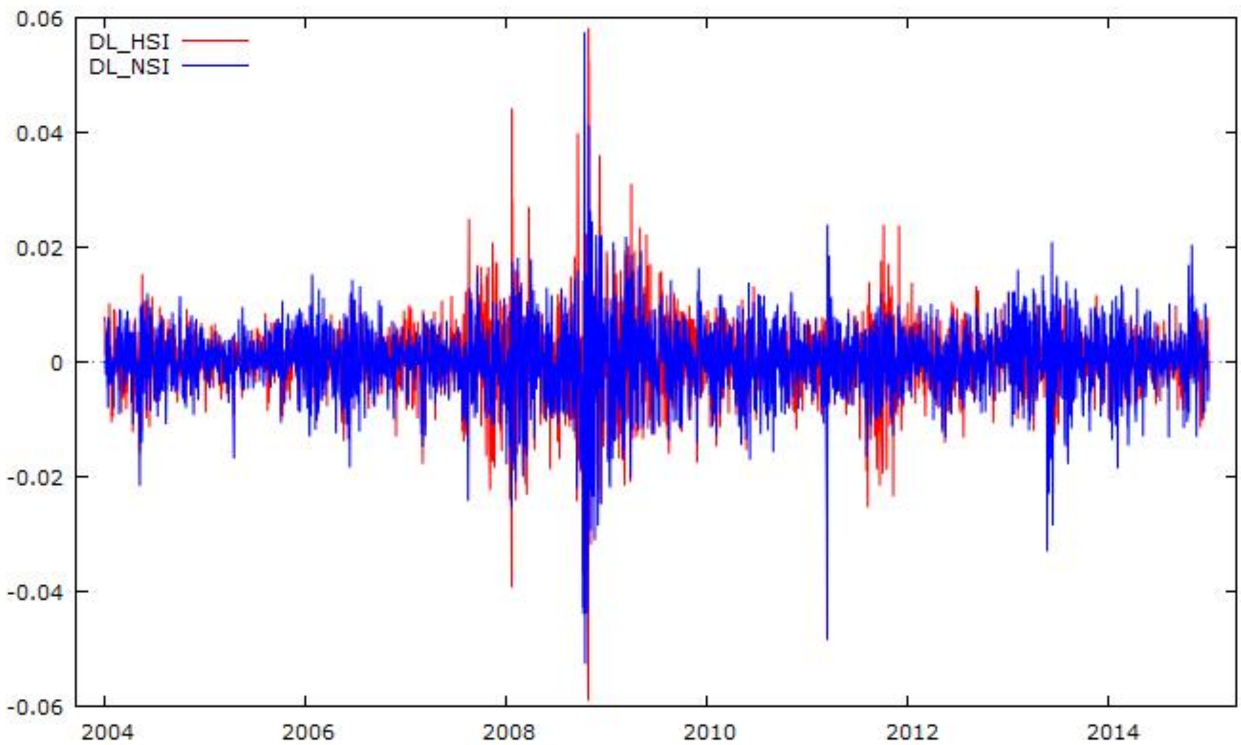
frequency distribution, found in Appendix 1.2. Finally, we note that the standard deviation of HSI is approximately 20% of the mean value whilst the comparable statistic for NSI is around 25%.

Under the null hypothesis of no correlation, the correlation matrix presents a value of 0.2561, indicating at least some level of positive correlation between the two markets. This is supported by the t-value of 14.187, which is significant at the 1% level. As mentioned, it is the intention of the analysis of this paper to examine the correlations between the values of each stock market in further detail, over various data frequencies during both tranquil and crisis periods defined by the MSVAR analysis.

Conducting an Augmented Dickey-Fuller (ADF) test for a unit root in the sample series', we are unable to reject the null hypothesis of nonstationarity in the mean and therefore conclude that there exists a unit root in both time series'. [13] Results of this test for all data frequencies can be found in Appendix 1.4.

Following the conventional approach, we calculate first differences of the logarithms of stock prices in order to achieve stationarity (Caporale et al (2005), Chiang et al (2007)). Repeating the ADF test we are now able to reject the null, concluding that our data exhibits stationarity in the logarithmic differences and we can proceed with our analysis on this basis. This technique reduces the persistence of heteroskedasticity which is often the cause of a number of issues for analysis of financial data (Fama (1963), French, Schwert and Stambaugh (1987)).

Figure 3: First Differences Logarithms of HSI and NSI (DL_HSI and DL_NSI)



[13] The ADF test is statistically more powerful than the earlier Dickey-Fuller test as it overcomes problems associated with autocorrelation, by including lags of the dependent variable as explanatory variables. The test statistic used is the common t-statistic, using alternative critical values adopted to reflect the non-normal distribution under the null hypothesis of a unit root (Elder and Kennedy: 2001).

Finally, it is important to note that following Billio and Caporin (2010), this paper considers the markets of Hong Kong and Tokyo to be simultaneous, although it is understood that this is not strictly the case. It is anticipated that this has minimal impact when analysing correlation using daily data, and negligible or no impact when using lower frequencies of data.

4. Methodology

The following section outlines the empirical methodology that is adopted in this paper. Some justifications for the econometric techniques used have already been provided in Section 2, but will be expanded upon here. The majority of econometric modelling for this paper has been conducted using the R software package, with further analysis conducted in Gretl.

This paper takes two steps to determine the existence of contagion between the major stock markets of Hong Kong and Tokyo. First, it is necessary to distinguish between periods in the data when the markets are in crisis, and when they are not. Second, it is necessary to measure correlations between the markets during each of these periods, comparing the fluctuations. Using the Forbes and Rigobon definition of financial contagion, an increase in correlation during a crisis period is used as an indicator of financial contagion across markets.

In order to execute the first stage of our analysis, we construct a Markov switching (MS) model with Bayesian vector autoregression (BVAR). The MS model (Hamilton 1989) has been widely used by economists to model non-linear time series'. The method incorporates multiple equations to define behaviours of different regimes over time, capturing dynamic patterns by allowing switching between each structure. The model contrasts that of its commonly used alternative (Quandt 1972) which performs random time-independent switching, as opposed to the regulated approach performed by the Markovian model (Kuan 2002). It is widely agreed that the Markov switching model is highly suited to describing data which display discrete dynamic patterns over different periods of time, which justifies its selection for the research of this paper.[14]

As stated, the methodology used in this paper to determine regime changes within our data follows the work of Zhou et al (2014), who combine Markov switching mechanisms with VAR models to examine correlations between Hong Kong, Shanghai and US stock markets, finding regimes for bull and bear markets between 2005 and 2013.

For consistency, and following the methodology of previous research (e.g. Khalid and Kawai 2003), all VAR models in this paper are estimated using a single lag such that $p = 1$. Although Fama's original hypothesis of perfectly efficient markets (Fama 1970) has been widely contested and there is still much disagreement on this subject (Shiller 2003), there is a strong and compelling economic argument that financial markets react quickly to the introduction of new information (Malkiel 2003). In most cases, this choice of lag-length is supported by the selection criteria, which can be found in Appendix 1.5. As the models estimated do not include any exogenous variables, the VAR process is conducted using OLS estimation. Here, we describe the construction of the MSBVAR model to be employed in the current analysis. The model aims to establish the dynamic process of an observed

[14] As the work of this paper considers a recession period, traditional structural break tests such as the Chow or Quandt Likelihood Ratio tests are less appropriate. See Kuan (2002) for a good account of the applications and uses of the Markov switching model in the existing literature.

time series y_t and a discrete state variable s_t for $t = 1 \dots T$ by jointly constructing the general probability $\Pr(y_t, s_t)$ and separating the information of the conditional probabilities $\Pr(y_t | s_t)$ and $\Pr(s_t | y_t)$. The model generates a transition matrix Q, with each element giving the probability of a transition between states $\Pr(s_t = i | s_{t-1} = j)$. The transition matrix and the Markov model are thus constructed as:

$$\mathrm{Q} = \begin{bmatrix} pr_{ii} & pr_{ij} \\ pr_{ji} & pr_{jj} \end{bmatrix}$$

$$\Pr(y_t | \Theta, Q) = \prod_{t=1}^{T} \left(\sum_{s_t=1}^{h} \Pr(y_t | \mathrm{Y}_{t-1}, \Theta, s_t) \times \Pr(y_t | \mathrm{Y}_{t-1}, \Theta, Q) \right)$$

Variable	Definition
y_t	The observed time series at time t for $t = 1 \dots T$
h	Maximum number of regimes required to account for potential phase dynamics
Θ	Set of regime-specific dynamic parameters $\Theta = (\theta_1, \theta_2 \dots \theta_h)$
Q	$h \times h$ Markov transition matrix whose rows sum to 1
s_t	Discrete state variable for each t

The MS model uses the Expectation Maximisation (EM) algorithm to iteratively approximate the maximisation of the likelihood function, allowing mixed distributions within the data set (i.e. the value of each observation is known, but its distribution is not). Ehrmann, Ellison and Valla (2003) note that “since the Markov chain is hidden, the likelihood function has a recursive nature: optimal inference in the current period depends on the optimal inference made in the previous period. Under such conditions the likelihood cannot be maximised using standard techniques.” The EM algorithm comprises two steps, which it ‘bounces’ between, to estimate the model parameters through the likelihood function, under the presence of latent variables. The first step estimates the latent variables, given the observed data and suggested parameters $\Pr(y_t | \mathrm{Y}_{t-1}, \Theta, s_t)$, while the second estimates the parameters, given the latent variables and the observed data $\Pr(y_t | \mathrm{Y}_{t-1}, \Theta, Q)$ (Brandt and Freeman 2012). We estimate the model using 30 iterations of the EM algorithm, which turns out to be more than sufficient. We follow the most popular assumption, that these latent regime probabilities follow a first-order Markov process.[15]

From the generalised model above, we construct a regime specific Bayesian VAR model, under a number of restrictions such as controlling the standard deviation around the AR(1) parameter and the lag decay.

The Bayesian approach to VAR analysis allows parameters of the model to be considered as random variables. Typical VAR analysis is often constrained by the limited size of macroeconomic data sets which are not compatible with models with large numbers of parameters. The Bayesian method tackles this over-parameterisation problem by assigning initial probabilities to many parameters. The BVAR methodology is widely popular in econometric analysis of macroeconomic and financial data (Canova 2007). Although it is possible to determine Markov regime changes using a traditional VAR model, construction of a BVAR model in this instance will reduce the complexities involved with future extensions of this model, which could include a number of exogenous macroeconomic factors.

[15] This assumption is widely used in a variety of applications, for example Krolzig (1997) and Girardin and Moussa (2008).

The switching process uses a blockwise optimisation procedure whereby joint optimisation is partitioned into four separate modules, maximising over the regime-specific intercepts $c(s_t)$, the AR(1) coefficients $B_l(s_t)$, the error covariances $\Sigma(s_t)$ and the residuals $\in (s_t)$. (Sims, Waggoner and Zha 2008). The number of lags used in each VAR model is represented by $l = 1 \dots p$.

The general model estimated is then:

$$y_t = c(s_t) + \sum_{l=1}^{p} y_{t-l} B_l(s_t) + \in (s_t)$$

$$\in_t (s_t) \sim N\big(0, \Sigma(s_t)\big) \quad t = 1,2, \dots T.$$

The variance-covariance matrix is selected a-priori to be diagonal, which is not deemed to be a restrictive condition as the VAR models constructed do not include exogenous factors.

In line with previous studies (Boyer et al (2006), Rodriguez (2007), Mandilaras and Bird (2010)), we assume just two regimes; a tranquil period and a crisis period. In most cases, this approach is supported by the log-likelihood values. These are generally higher than those of the three regime estimations, which are estimated for completeness. Initial state probabilities are restricted as $1/h$.

This process is estimated using a simplified Sims and Zha optimisation which assigns probabilities on coefficients of lagged effects, deeming it appropriate to restrict the information set to include only a leading indicator of the price level (Leeper, Sims and Zha 1996). In this instance therefore, the prior indicates that the time series is best described by its most recent value (Brandt and Freeman 2006). This optimisation technique has been widely used in the literature on BVAR models and is commonly accepted to produce good forecasts for financial variables (Kapetanios et al 2012) but in the single lag model with no exogenous variables, the number of restrictions required is significantly reduced. The Sims and Zha optimisation restrictions we impose (denoted by λ) are:

Restriction	Value
$\lambda_0 = 0.80$	Overall tightness of the prior (0,1)
$\lambda_1 = 0.15$	Standard deviation of prior around AR(1) parameters
$\lambda_2 = 1.00$	Lag decay ($\lambda_2 > 0$)
$\lambda_3 = 0.20$	Standard deviation around the intercept ($\lambda_3 > 0$)

Using the same restrictions, the MSBVAR model is constructed for a number of data frequencies, lag orders and regimes. As mentioned, only duel-regime, single-lag models are analysed in this paper. Models with additional lags and regimes are constructed for completeness and in many cases prove to be less statistically significant than the chosen alternative. Future analysis could be conducted building the above model with different assumptions, based on these log likelihood values. Details of these additional models and their log-likelihood values can be found in Appendix 1.6.[16]

Specifically, the models constructed for DL_HSI and DL_NSI are as follows:

$$DL\_HSI_t = \ c_{HSI}(s_t) + DL\_HSI_{t-1} B_1(s_t) + \in_{HSI} (s_t)$$

[16] From the graphs it is clear to see that often the stock markets are estimated to exist within the third regime with a probability close to zero for the whole time period analysed. Full results of MSBVAR estimations are not included due to size (comprising over 25,000 values for the daily frequency data alone) but are available upon request.

$$DL\_NSI_t = \ c_{NSI}(s_t) + DL\_NSI_{t-1}B_2(s_t) + \epsilon_{NSI}\ (s_t)$$

In the second stage of the analysis, we employ both the Pearson and Spearman measures of correlation to measure the levels of comovement between the two data sets. The Pearson coefficient is used as a measure of linear correlation between two variables, calculated as their covariance, divided by the product of their standard deviations.

$$\rho_{DL_{HSI},DL_{NSI}} = \frac{Cov(DL_{HSI}, DL_{NSI})}{\sigma_{DL\_HSI}\sigma_{DL\_NSI}}$$

This method is used by Hon, Strauss and Yong (2004) in their analysis of financial contagion resulting from the September 11th terrorist attacks in the United States. They calculate significant increases in correlation in the post-crisis period, with these 'excess' correlations typically dispersing within a few months.

Li (2009) notes that the Pearson measure's ability to only capture linear correlations has the potential to be restrictive and can miss important dimensions of the financial contagion phenomenon. We therefore also simultaneously calculate the Spearman measure of correlation, which captures monotonic relationships by ranking observations against each other. This can also reduce the impact caused by outlying observations on the results, when compared to the Pearson measure. The Spearman coefficient is calculated as:

$$\rho = 1 - \frac{6\sum(dl_{HSI} - dl_{NSI})^2}{n(n^2-1)}$$

Here, the lower case dl indicates the calculation focusses on the ranking of the observations of the variables, rather than the values, as in the Pearson measure. The coefficients are calculated based the sample size n. Values of both coefficients range between -1 and 1. By our definition, financial contagion between markets is characterised by an increase in correlation during a crisis period (Forbes and Rigobon 2002).

We anticipate to find that market correlations increase during crisis periods identified by the MSBVAR models, when compared to preceding and subsequent periods of tranquillity, that is, we expect to find evidence of financial contagion using the methodology outlined above. Additionally, it is supposed that there will be a marked difference in the levels of observed correlation, which is decreasing as the frequency of the data becomes less dense. This is in line with the results of existing literature, such as that of Chu, Chan and Sin (2000).

5. Results

The following section presents the results of the analysis outlined above, structured across each data frequency. The timings and durations of crisis periods observed by the MSBVAR calculations are greatly influenced by the frequency of the time series being analysed and so it is necessary to use different criteria for their definition under each data frequency.

5.1 Daily Observations

With daily and even weekly data, exact crisis periods for both markets are noticeably difficult to observe. The MSBVAR process indicates probabilities of switching between regimes but fluctuations within market prices lead to the MS analysis indicating numerous regime switches within the relatively high frequency data. The MSBVAR output using daily observations is shown in Figures 4 and 5, for DL_HSI and DL_NSI respectively.

Figure 4: MSBVAR Output for DL_HSI – p=1, h=2

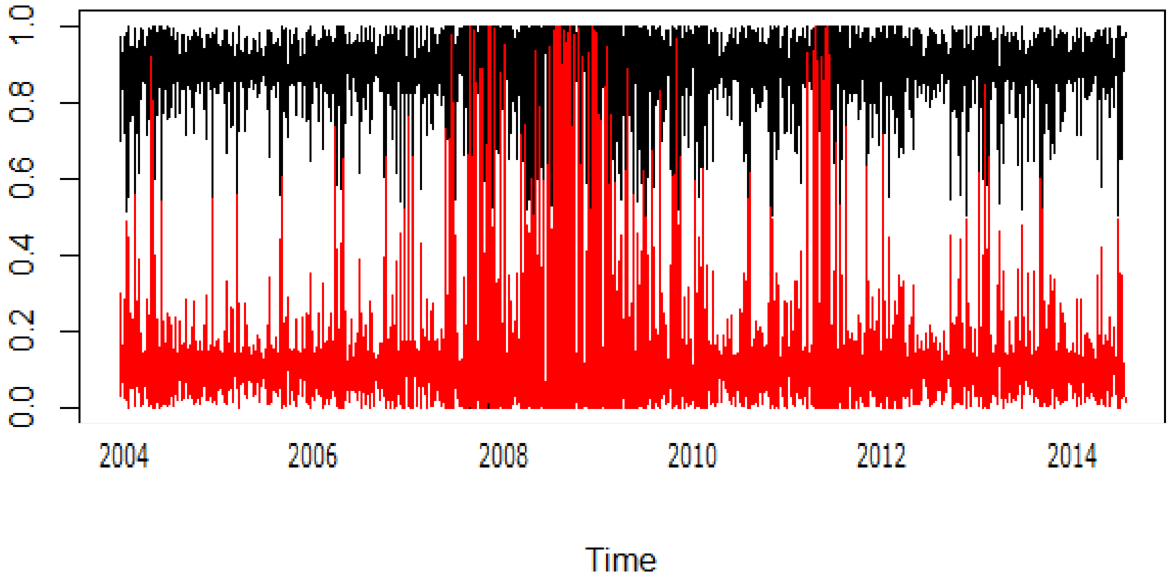
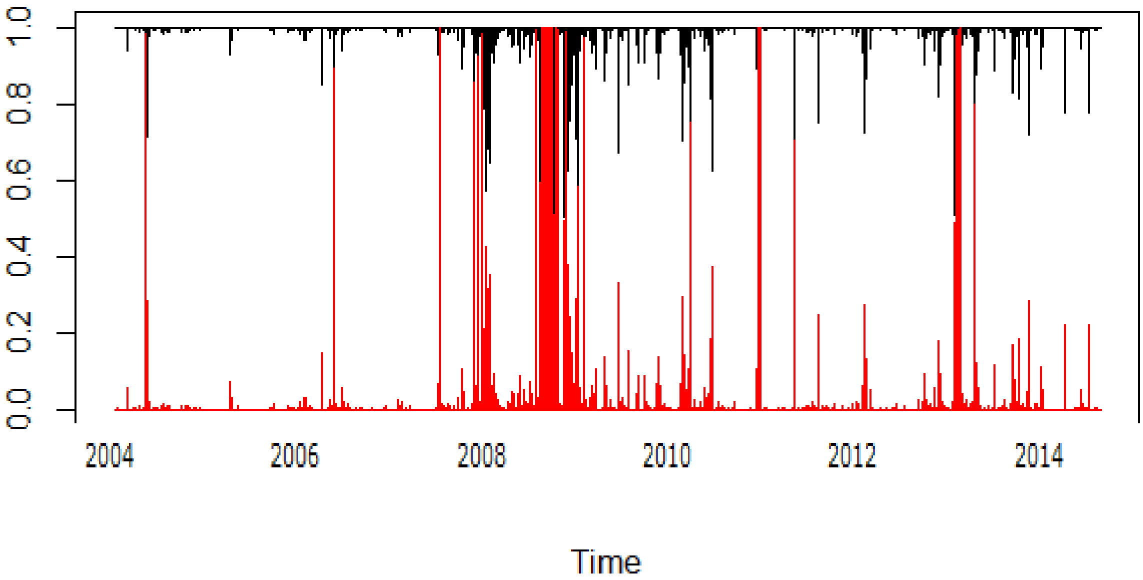


Figure 5: MSBVAR Output for DL_NSI – p=1, h=2



It is proposed that a crisis period is observed when the MSBVAR model indicates a probability ≥ 0.5 of the market being in the alternative regime for a proportion of periods greater than 50%, over a minimum of five observations. Within the Hang Seng daily data we observe nine such periods from the 2868 observations. There is much lower volatility within MSBVAR probabilities generated from the Nikkei 225 data, with the model indicating a high probability of DL_NSI remaining in one regime for the majority of the analysed time period. The correlations during tranquil and crisis periods are documented below in Figure 6.

Figure 6: Pearson and Spearman correlations based on MSBVAR analysis Frequency = Daily

Start	End	Obs.	Pearson	Spearman	Period
05/01/04	31/12/14	2868	0.584361	0.502596	Total
05/01/04	27/02/07	822	0.512251	0.456839	Tranquil 1
28/02/07	06/03/07	5	0.674774	0.600000	Crisis 1
07/03/07	11/01/08	223	0.627420	0.589670	Tranquil 2
14/01/08	23/01/08	8	0.972954	0.928571	Crisis 2
24/01/08	04/02/08	8	0.574632	0.619048	Tranquil 3
05/02/08	15/02/08	9	0.853050	0.811723	Crisis 3
18/02/08	05/09/08	145	0.608904	0.543911	Tranquil 4
08/09/08	22/09/08	11	0.786907	0.572727	Crisis 4
23/09/08	06/10/08	10	0.068366	0.200000	Tranquil 5
07/10/08	31/10/08	19	0.709034	0.771930	Crisis 5
03/11/08	05/01/09	46	0.738175	0.634162	Tranquil 6
06/01/09	22/01/09	13	0.631866	0.620879	Crisis 6
23/01/09	02/03/09	27	0.441037	0.468540	Tranquil 7
03/03/09	25/03/09	17	0.672453	0.718137	Crisis 7
26/03/09	22/04/09	20	0.721424	0.539301	Tranquil 8
23/04/09	08/05/09	12	0.413642	0.103219	Crisis 8
11/05/09	03/08/11	583	0.534200	0.549289	Tranquil 9
04/08/11	10/08/11	5	0.589936	0.300000	Crisis 9
11/08/11	22/09/11	31	0.695930	0.680645	Tranquil 10
23/09/11	10/10/11	12	0.850113	0.851140	Crisis 10
11/10/11	31/12/14	842	0.441796	0.428870	Tranquil 11

In some instances, the data appear to evidence herding behaviour. For example, the correlation during the first tranquil period is 0.512 (by the Pearson measure), but rises to 0.627 in the subsequent tranquil period, following a crisis. Additionally, tranquil period correlation rises from 0.441 in period 7 to 0.721 in period 8. These outputs can be taken as evidence of herding behaviour, where increases in correlation during periods of financial crisis persist, even after the regime is deemed to have switched back to a tranquil period.

Some correlation coefficients should be interpreted with further caution. For example in the fifth tranquil period, the Pearson measure of correlation is 0.068, which is markedly lower than during all other periods of tranquillity. This is likely due to the small number of observations within this period.

From these correlations, we take mean and weighted averages of both the tranquil and crisis periods to observe our calculated market correlations as below in Figure 7. There is noticeable difference in correlation coefficients, with crisis period correlations estimated to be much higher than during tranquil periods, using both the Pearson and Spearman measures.

Figure 7: Average Correlation Coefficients. Frequency = Daily

	Pearson		Spearman		
Obs.	Av. Corr.	W-Av. Corr.	Av. Corr.	W-Av. Corr.	Period
2868	0.584361	-	0.502596	-	Total
2757	0.545188	0.515000	0.519116	0.488897	Tranquil
111	0.715473	0.709219	0.627833	0.648043	Crisis

5.2 Weekly Observations

Adopting the same process using weekly observations, a number of crisis periods are observed within the data. Again, we define a period of crisis as the Markov model indicating high probability of persistence in the alternative regime of at least three periods over a minimum of five observations but this time include that a crisis period can also be observed when there is high probability of persistence in the alternative regime for three periods consecutively. Observed crisis periods within this dataset are generally relatively short, lasting between five and 11 weeks. Graphical representation of the probabilities for the complete time period can be found in Appendix 1.7, and a summary is provided below in Figure 8.

Figure 8: Pearson and Spearman correlations based on MSBVAR analysis Frequency = Weekly

Start	End	Obs	Pearson	Spearman	Period
19/01/04	29/12/14	572	0.655699	0.563454	Total
19/01/04	10/05/04	17	0.289842	0.291667	Tranquil 1
17/05/04	11/06/04	6	0.903360	0.885714	Crisis 1
18/06/04	07/01/08	185	0.542815	0.446384	Tranquil 2
14/01/08	18/02/08	6	0.654260	0.314286	Crisis 2
25/02/08	15/09/08	30	0.704670	0.680979	Tranquil 3
22/09/08	03/11/08	7	0.934716	0.892857	Crisis 3
10/11/08	22/12/08	7	0.821880	0.857143	Tranquil 4
29/12/08	13/04/09	16	0.803096	0.687500	Crisis 4
20/04/09	25/10/10	80	0.709726	0.667440	Tranquil 5
01/11/10	29/11/10	5	0.633417	0.400000	Crisis 5
06/12/10	10/10/11	45	0.650822	0.684717	Tranquil 6
17/10/11	05/12/11	8	0.924322	0.785714	Crisis 6
12/12/11	04/06/12	26	0.651988	0.522051	Tranquil 7
11/06/12	30/07/12	8	0.535285	0.428571	Crisis 7
06/08/12	29/12/14	126	0.420812	0.415446	Tranquil 8

Again, correlations during crisis periods tend to be higher than those during periods of tranquillity. This trend is captured by both the Pearson and Spearman measures although is not true across all subsamples. The most striking increase is evident in the first crisis period, where the Pearson and Spearman correlations are three times greater than in the initial period of tranquillity.

There is also some evidence to support the theory of herding, with a number of instances whereby correlation coefficients following a crisis are higher than during the period immediately preceding the crisis. For example, the Pearson coefficient indicates a correlation of around 0.543 in the second tranquil period but this figure rises to 0.705 immediately following the observed crisis period. A similar story can be told following the third observed period of crisis, where the correlation coefficient for the tranquil period rises from 0.705 before, to 0.822 afterwards.

However, the results indicate that this herding behaviour does not always occur and indeed might not be persistent as otherwise market correlations would tend towards 1, under the presence of both contagion and herding behaviour.

Calculating weighted averages of these correlations, it is clear that the two markets exhibit higher correlation during crisis periods.

Figure 9: Average Correlation Coefficients. Frequency = Weekly

	Pearson		**Spearman**		
Obs.	Av. Corr.	W-Av. Corr.	Av. Corr.	W-Av. Corr.	Period
572	0.655699	-	0.563454	-	Total
516	0.599069	0.558683	0.570728	0.511813	Tranquil
56	0.755407	0.778254	0.615666	0.645791	Crisis

5.3 Fortnightly Observations

Although it is still hypothesised that financial contagion will be observed within the lower frequency datasets, it is anticipated that the differences in correlation coefficients between periods of crisis and tranquillity will be smaller. This follows the work of Chu, Chan and Sin (2000), who note that contagion effects are less likely to be captured by lower-frequency data.

Interestingly, the fortnightly data indicates the existence of a number of sustained crisis periods for both the Hong Kong and Tokyo markets, sufficient that the MSBVAR estimations indicate crisis periods occurring in one or both markets for the majority of the 11-year span of data analysed, using the same criteria defined previously for weekly observations.

Overall, the trend of increasing market correlations during crisis periods is consistent with the previous analysis using daily and weekly data. One instance of negative correlation is observed, between 22nd April and 20th May 2013, although this is likely a result of the very small size of this data subset, rather than an indicator that the stock markets of Hong Kong and Tokyo experience a negatively correlated relationship.

Figure 10: Pearson and Spearman correlations based on MSBVAR analysis Frequency = Fortnightly

Start	End	Obs	Pearson	Spearman	Period
09-Feb-04	29-Dec-14	285	0.634396	0.530204	Total
09-Feb-04	09-Feb-04	14	0.255818	0.261539	Crisis 1
23-Aug-04	01-May-06	45	0.154233	0.130567	Tranquil 1
15-May-06	10-Jul-06	5	0.584563	0.600000	Crisis 2
24-Jul-06	23-Jul-07	27	0.390820	0.090965	Tranquil 2
06-Aug-07	14-Mar-11	95	0.772972	0.689091	Crisis 3
28-Mar-11	18-Jul-11	9	0.369584	0.083333	Tranquil 3
01-Aug-11	24-Sep-12	31	0.722377	0.727823	Crisis 4
08-Oct-12	25-Feb-13	11	0.117981	0.218182	Tranquil 4
11-Mar-13	08-Apr-13	3	0.973759	1.000000	Crisis 5
22-Apr-13	20-May-13	3	-0.849809	-0.500000	Tranquil 5
03-Jun-13	24-Feb-14	20	0.558055	0.566917	Crisis 6
10-Mar-14	22-Sep-14	15	0.378815	0.460714	Tranquil 6
06-Oct-14	17-Nov-14	4	0.582592	0.800000	Crisis 7

01-Dec-14	29-Dec-14	3	0.703108	0.500000	Tranquil 7

Again, it is noted that correlations are on average, much greater during crisis periods. Strikingly, the difference in these averages is much greater than those observed with the daily and weekly data, which contradicts the observations of Chu, Chan and Sin (2000).

Figure 11: Average Correlation Coefficients. Frequency = Fortnightly

	Pearson		Spearman		
Obs.	Av. Corr.	W-Av. Corr.	Av. Corr.	W-Av. Corr.	Period
285	0.634396	-	0.530204	-	Total
113	0.180676	0.242113	0.140537	0.162764	Tranquil
172	0.635734	0.690367	0.663624	0.652477	Crisis

5.4 Monthly Observations

With data of lower frequency we tend to only observe a single crisis period, although it is much longer for both the monthly and quarterly analysis than for the higher frequency data. This is indicated in Figures 11 and 12 which show the MSBVAR outputs for both markets. The picture is much clearer for the Hong Kong market, with the Tokyo market exhibiting greater fluctuation in regime probabilities, which peaks during 2008/09; the period associated with the global financial crisis.

Figure 11: MSBVAR Output for DL_HSI – p=1, h=2

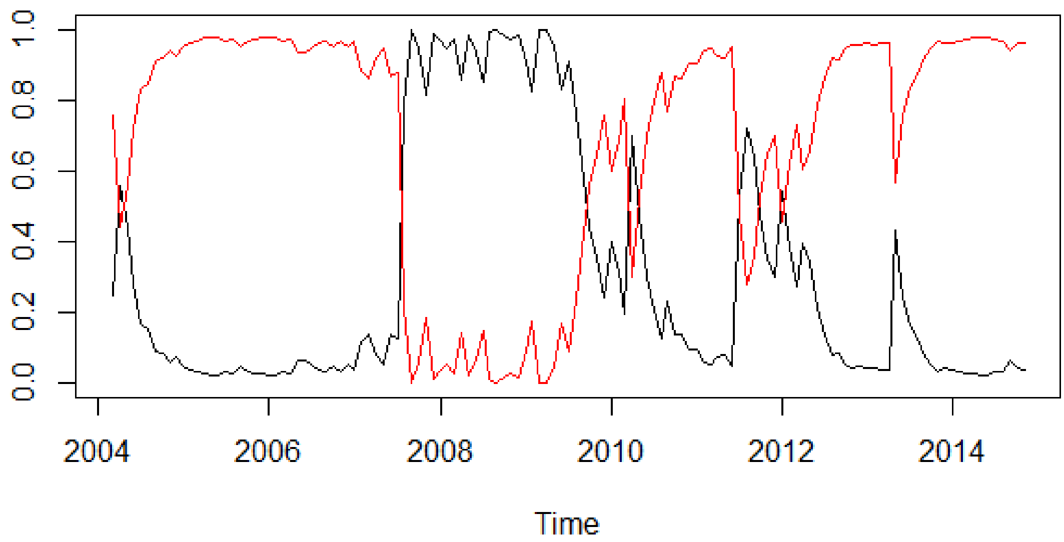
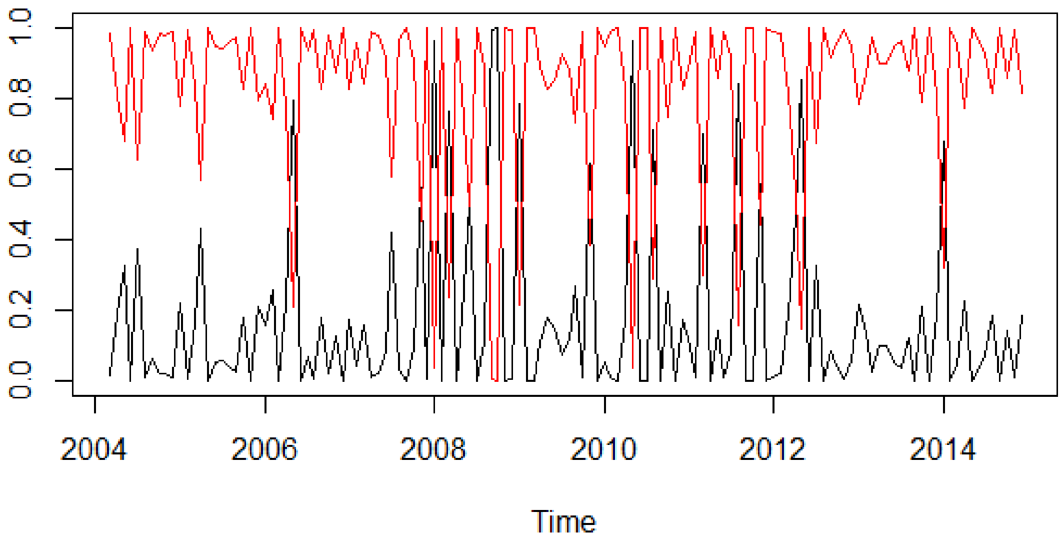


Figure 12: MSBVAR Output for DL_NSI – p=1, h=2



The Pearson correlation analysis between DL_HSI and DL_NSI over the complete time period indicates a value of 0.530, although the calculated Spearman coefficient indicates a lower level of correlation, at 0.361. This indicates that the two markets exhibit a more linear relationship, which is captured by the Pearson coefficient.

Specifically, the correlation during the crisis period is significantly higher (by both measures) than during the tranquil period. Some of this increased correlation appears to persist in a linear fashion, during the second tranquil period. The results in Figure 14 confirm that average correlation between the two markets is much lower during tranquil periods.

Figure 13: Pearson and Spearman correlations based on MSBVAR analysis Frequency = Monthly

Start	End	Obs	Pearson	Spearman	Period
Feb-04	Dec-14	131	0.530019	0.361159	Total
Feb-04	Jul-07	42	0.132442	0.183371	Tranquil 1
Aug-07	Sep-09	26	0.816354	0.794872	Crisis 1
Oct-09	Dec-14	63	0.299206	0.183372	Tranquil 2

Figure 14: Average Correlation Coefficients. Frequency = Monthly

	Pearson		Spearman		
Obs.	Av. Corr.	W-Av. Corr.	Av. Corr.	W-Av. Corr.	Period
131	0.530019	-	0.361159	-	Total
105	0.215824	0.232500	0.183372	0.183372	Tranquil
26	0.816354	0.816354	0.794872	0.794872	Crisis

Quarterly Observations

In both cases, estimating quarterly data using a three-regime model served to prove the ineffectiveness of this specification in describing market dynamics, generating log-likelihood ratios significantly lower than the equivalent two period models. Japanese data indicate a crisis period occurring across five observations between Q3 2007 and Q3 2008. Data from Hong Kong indicates a slightly longer period of crisis affecting the Hang Seng's returns, occurring between Q4 2007 and Q2 2009. Estimates of correlation are calculated for the total period when either one or both markets are in crisis and are shown in Figure 15. Looking at the crisis period, the differences between the Pearson and Spearman figures are noticeably greater than with higher frequency data. This is to be expected as the presence of a few outlying data points can have a much larger impact on the calculated correlation coefficient when the sample size is small and therefore the 'corrections' made by the Spearman calculations are more noticeable.

Additionally, the small and relatively crude properties of the sample in this instance also provide explanation for the negative correlations found during the crisis period, appearing to indicate that a crisis in one market can cause an increase in stock prices in the other. The assumptions underlying our analysis of financial contagion indicate that this is not thought to be the case and so we remain cautious in interpreting the results in this manner. It is much more likely that the use of quarterly time series data is not appropriate for this kind of stock market analysis. This is supported by its lack of use in the existing empirical literature. Nevertheless, correlation between the observed markets increases in **absolute** terms during a crisis period, but this result is caveated by Boyer et al (1999) who state that short sampling periods can affect the ability to accurately observe financial contagion.

Figure 15: Pearson and Spearman correlations based on MSBVAR analysis Frequency = Quarterly

Start	End	Obs	Pearson	Spearman	Period
Q3 2004	Q3 2014	43	0.096610	0.074902	Total
Q3 2004	Q2 2007	12	0.375051	0.372400	Tranquil 1
Q3 2007	Q2 2009	8	-0.314540	-0.457360	Crisis 1
Q3 2009	Q4 2014	23	0.143227	0.115812	Tranquil 2

Figure 16: Average Correlation Coefficients. Frequency = Quarterly

	Pearson		Spearman		
Obs.	Av. Corr.	W-Av. Corr.	Av. Corr.	W-Av. Corr.	Period
43	0.096610	-	0.074902	-	Total
35	0.259139	0.222710	0.244106	0.203785	Tranquil
8	-0.314540	-0.314540	-0.457360	-0.457360	Crisis

Combining the results to examine the existence of financial contagion over multiple data frequencies, it is clear that the frequency of data modelled has a significant impact on the results. This is in line with numerous previous works such as that of Chu, Chan and Sin (2000). Figures 17 and 18 graphically depict these final results, split by data frequency. Summaries of these graphs can be found in Appendix 1.8. In each case, the average absolute values of the correlation coefficient are notably larger during crisis periods, than tranquil ones. This is clear evidence of the existence of financial contagion, by the definition given by Forbes and Rigobon (2002). Interestingly, contrary to the research of Chu, Chan and Sin (2000), the difference in correlations between tranquil and crisis periods is much larger when analysing the lower-frequency data, with the greatest difference being observed in the monthly frequency, by both correlation measures. It is possible that the increased volatility exhibited by the high frequency data leads to lower correlations between markets, than are to be observed in lower-frequency data. However, this cannot explain the relative size of the increase in correlations during crisis periods.

Figure 17: Weighted Pearson Correlations by Frequency

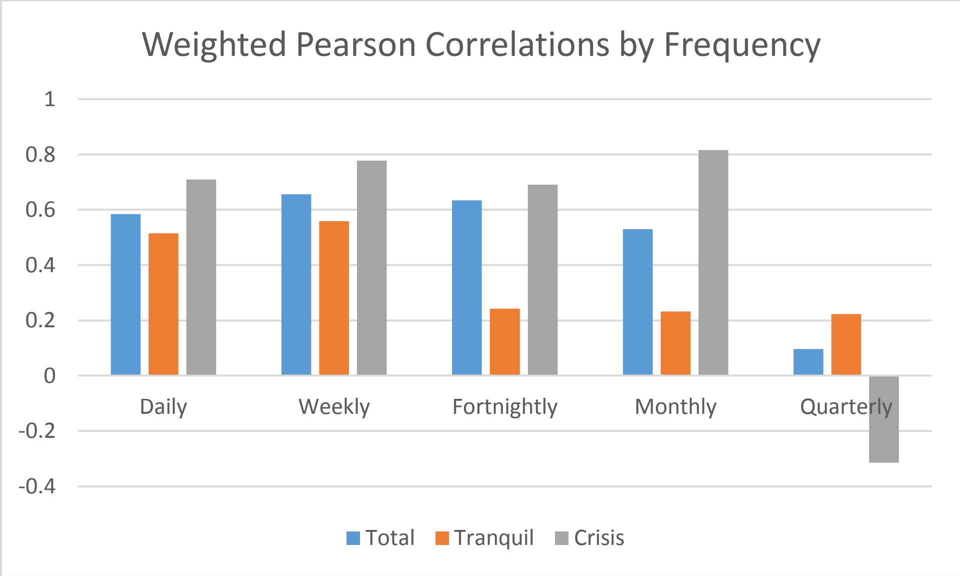
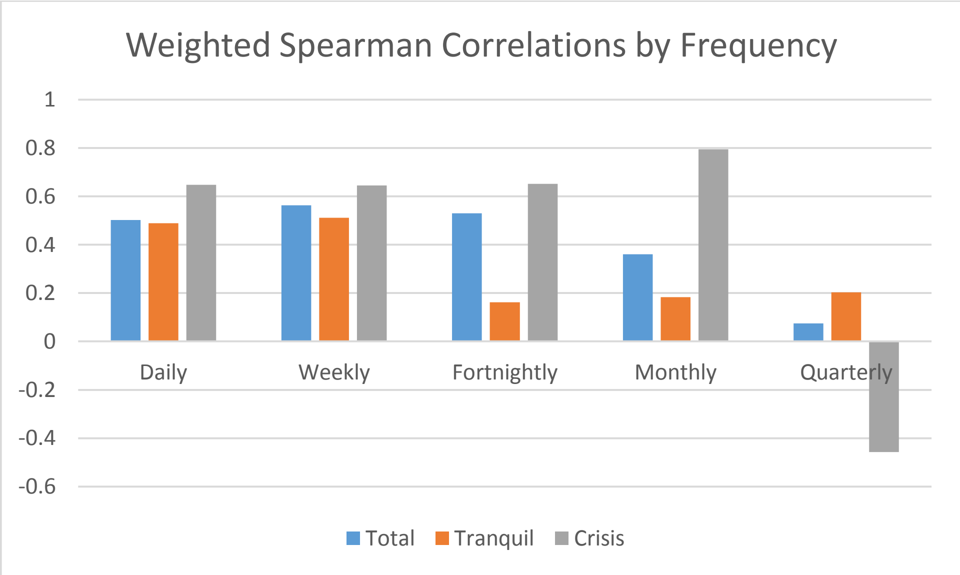


Figure 17: Weighted Spearman Correlations by Frequency



6. Concluding Remarks

This paper has examined the spread of the recent financial crisis between the stock markets of Hong Kong and Tokyo. Using multiple frequencies of price data obtained from the Hang Seng and Nikkei 225 indices, the paper constructed a MSBVAR model, to determine crisis periods of varying start time and duration. Market correlation dynamics are analysed using Pearson and Spearman techniques, with contagion evidenced by an increase in market correlation during a crisis period.

This paper both complements and adds to the existing literature by providing further use of MSBVAR techniques to determine regime switches within financial data sets. Additionally, analysis of financial contagion through comparison of correlations within varying data frequencies is apparently lacking within existing research. Much of the literature prefers to analyse different markets or time periods under the same frequency and so this work has taken the important step to understand implicitly how the frequency of a data set can affect the observation of financial contagion.

The results of this analysis are therefore relevant to academic researchers in determining the correct data frequency to use when conducting their research. Additionally, results on the observation of financial contagion have particular consequence to portfolio managers as the benefits of international diversification are significantly reduced under the existence of contagion across financial markets. Finally, the existence of financial contagion supports the case for financial assistance from international bodies such as the IMF, in order to halt the spread a financial crisis from one economy to another, although Corsetti et al (1998) note that this can create a risk of moral hazard.

The results of this paper serve to explain why the debate of the persistence and in fact existence of financial contagion remains alive. We have shown that the frequency of a time series dataset has a significant impact on the level of observed correlation and thus observation of financial contagion. The evidence has found that the correlation between the stock markets of Hong Kong and Tokyo increases during periods of crisis, regardless of the frequency of the observed time series, but that this increase is much greater when using lower-frequency data.

The intention of this paper was not to analyse the cause or transmission mechanism of contagion between financial markets. Therefore future studies could extend the methodology used in this paper by including exogenous macroeconomic factors in the MSBVAR model. This would enable more precise understanding of the factors contributing to market correlations, thus allowing researchers to correct for common exogenous shocks affecting both markets, which may not amount to financial contagion. Additionally, the work of this paper can be easily extended to analyse larger time periods, denser data frequencies or additional stock or other financial markets. Finally, the implementation of mean-reversion techniques would allow future researchers to more accurately understand the persistence of herding behaviour, following financial crises.

7. References

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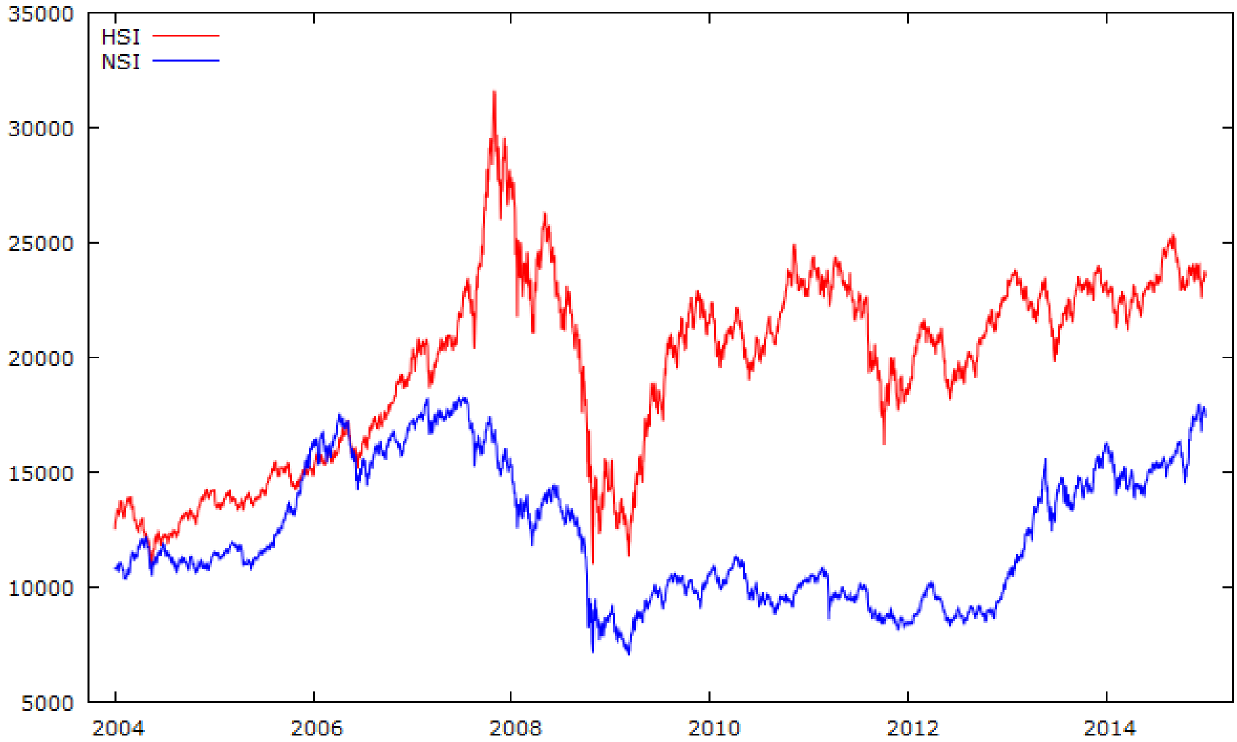
8. Appendix

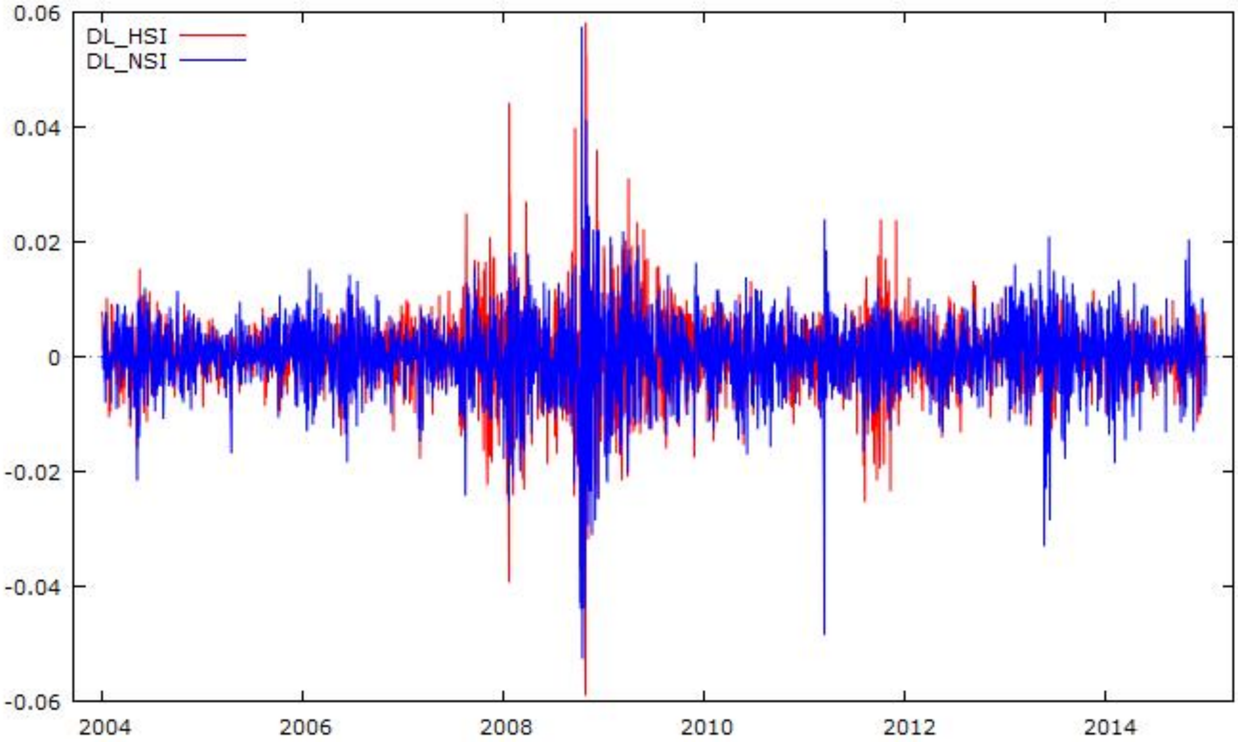
8.1 Time Series Plots and Summary Statistics

8.1.1 Daily Frequency – Levels



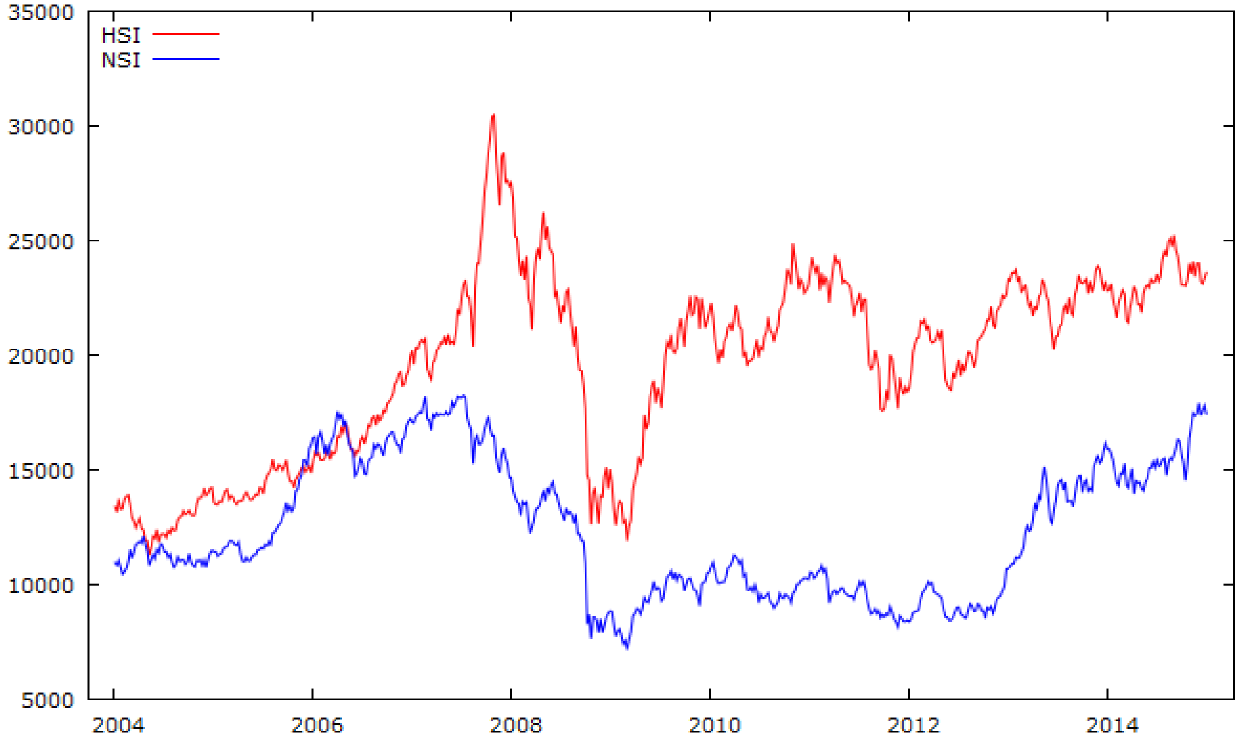
	Mean	Median	Minimum	Maximum
HSI	19587	20592	10968	31638
NSI	12345	11496	7055	18262
	Std. Dev.	C.V.	Skewness	Ex. kurtosis
HSI	4049.8	0.20676	-0.25741	-0.75535
NSI	2938.9	0.23807	0.32854	-1.2013
	5% perc.	95% perc.	IQ range	Missing obs.
HSI	12836	24703	6978.9	0
NSI	8542.4	17355	5316.8	0

1.1.2 Daily Frequency – First Differences of Logarithms



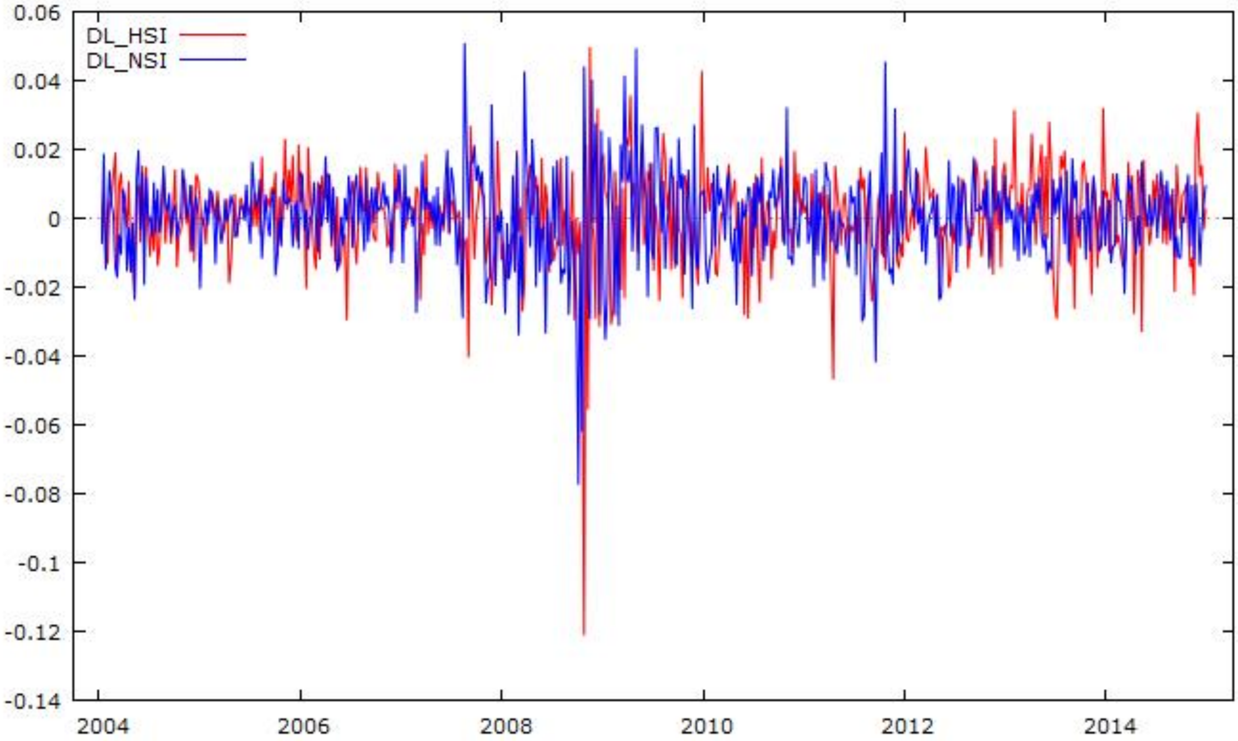
	Mean	Median	Minimum	Maximum
DL_HSI	0.000095317	0	-0.058988	0.058227
DL_NSI	0.000072283	0	-0.052598	0.057477
	Std. Dev.	C.V.	Skewness	Ex. kurtosis
DL_HSI	0.0065657	68.883	0.039296	10.452
DL_NSI	0.006502	89.952	-0.57104	8.9912
	5% perc.	95% perc.	IQ range	Missing obs.
DL_HSI	-0.010424	0.0091923	0.0055119	0
DL_NSI	-0.0098512	0.009458	0.0062179	0

1.1.3 Weekly Frequency – Levels



	Mean	Median	Minimum	Maximum
HSI	19606	20571	11277	30468
NSI	12355	11520	7173.1	18239
	Std. Dev.	C.V.	Skewness	Ex. kurtosis
HSI	4049	0.20651	-0.26321	-0.77335
NSI	2946.5	0.23848	0.32347	-1.2011
	5% perc.	95% perc.	IQ range	Missing obs.
HSI	12806	24776	6950.7	0
NSI	8535.9	17396	5326	0

1.1.4 Weekly Frequency – First Differences of Logarithms

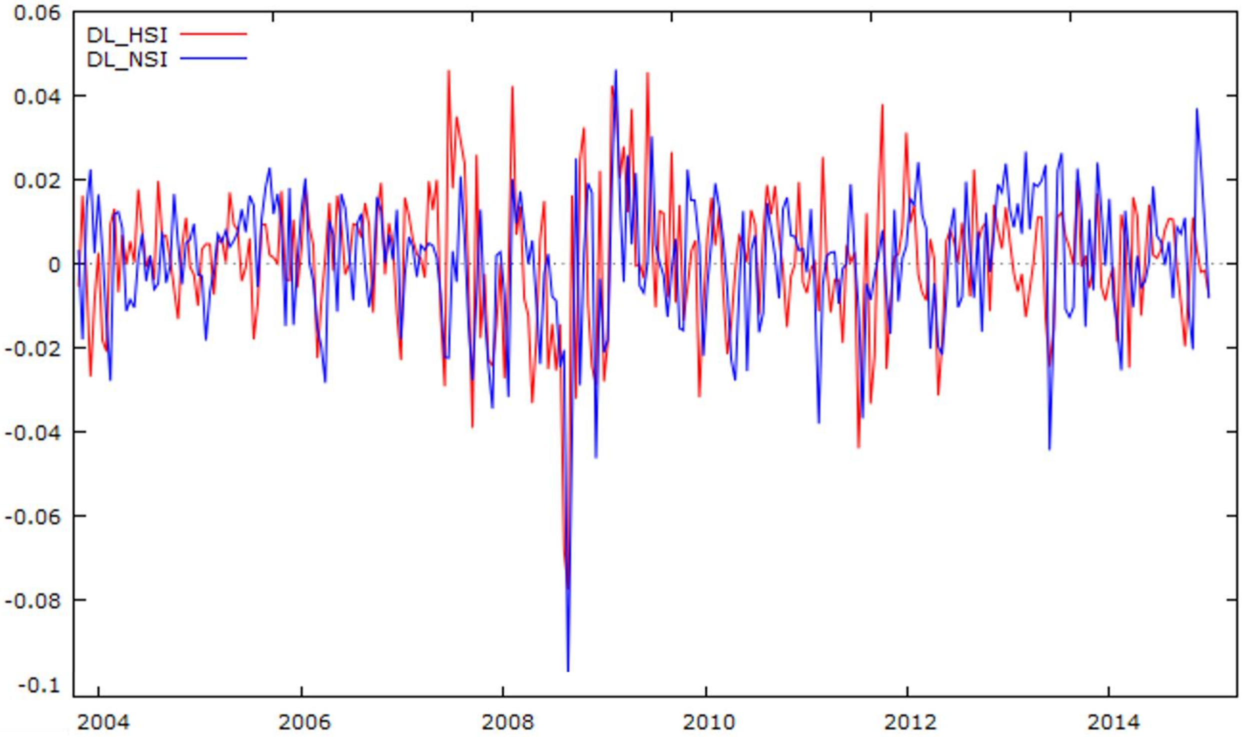


	Mean	Median	Minimum	Maximum
DL_HSI	0.00035258	0.001063	-0.1211	0.049725
DL_NSI	0.00043802	0.0017364	-0.077371	0.050894
	Std. Dev.	C.V.	Skewness	Ex.kurtosis
DL_HSI	0.013473	38.211	-1.5028	11.823
DL_NSI	0.013297	30.357	-0.35027	3.4818
	5% perc.	95% perc.	IQ range	Missing obs.
DL_HSI	-0.022255	0.018803	0.015299	0
DL_NSI	-0.020905	0.018748	0.016522	0

1.1.5 Fortnightly Frequency – Levels

	Mean	Median	Minimum	Maximum
HSI	19607	20616	11426	30437
NSI	12355	11457	7370.8	18190
	Std. Dev.	C.V.	Skewness	Ex. kurtosis
HSI	4042.1	0.20616	-0.2707	-0.78205
NSI	2943.9	0.23827	0.32216	-1.2091
	5% perc.	95% perc.	IQ range	Missing obs.
HSI	12859	24808	7067.4	0
NSI	8538	17393	5310.4	0

1.1.6 Fortnightly Frequency – First Differences of Logarithms

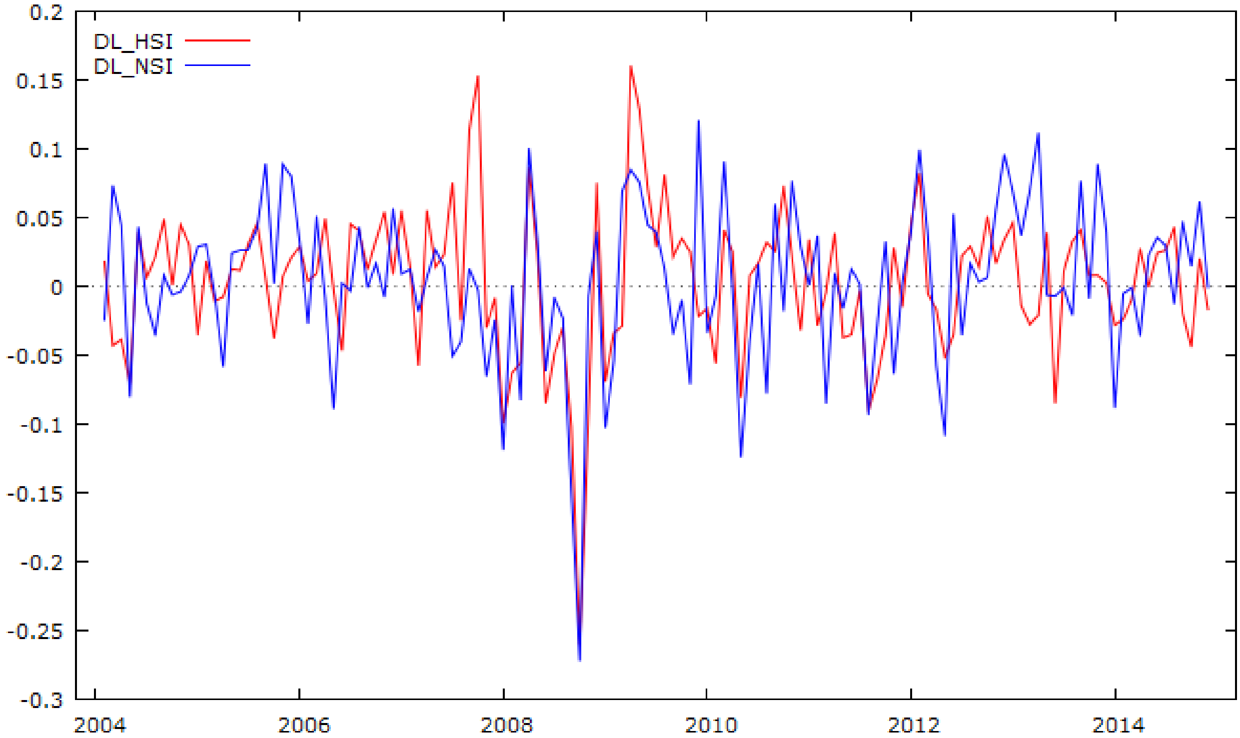


	Mean	Median	Minimum	Maximum
DL_HSI	0.00083188	0.0015128	-0.077475	0.046124
DL_NSI	0.00071096	0.0026076	-0.099108	0.046213
	Std. Dev.	C.V.	Skewness	Ex. kurtosis
DL_HSI	0.016249	19.533	-0.58625	2.7032
DL_NSI	0.015746	22.148	-1.186	5.186
	5% perc.	95% perc.	IQ range	Missing obs.
DL_HSI	-0.026403	0.025767	0.018109	0
DL_NSI	-0.025464	0.022605	0.020048	0

1.1.7 Monthly Frequency – Levels

	Mean	Median	Minimum	Maximum
HSI	19581.3	20479.9	11661.4	29152.6
NSI	12400.5	11484.4	7568.42	18138.4
	Std. Dev.	C.V.	Skewness	Ex. Kurtosis
HSI	4029.81	0.205799	-0.286875	-0.82887
NSI	2981.44	0.240429	0.322049	-1.26079
	5% Perc.	95% Perc.	IQ range	Missing obs.
HSI	12932.7	24878.9	7076.36	0
NSI	8532.07	17389.4	5451.03	0

1.1.8 Monthly Frequency – First Differences of Logarithms

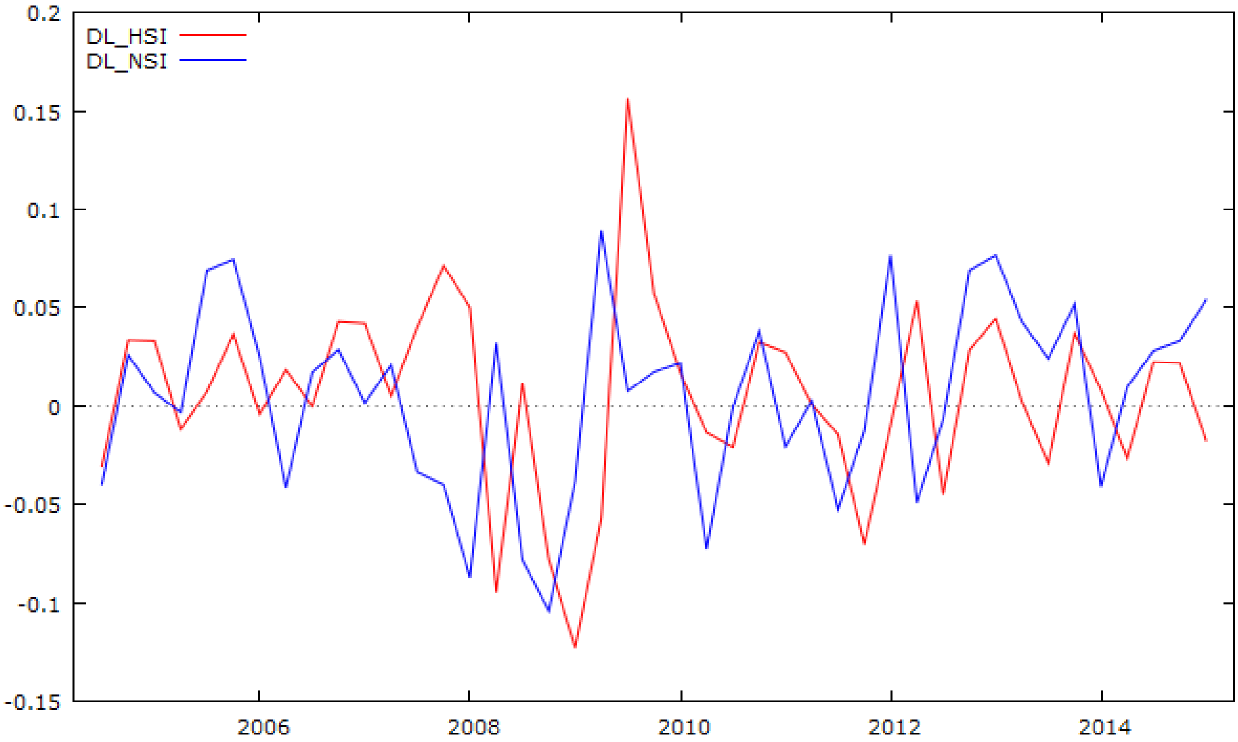


	Mean	Median	Minimum	Maximum
DL_HSI	0.0042907	0.01108	-0.26069	0.16055
DL_NSI	0.0037352	0.0039528	-0.27216	0.12089
	Std. Dev.	C.V.	Skewness	Ex. kurtosis
DL_HSI	0.053098	12.375	-0.70785	4.3246
DL_NSI	0.057693	15.446	-1.0244	3.1516
	5% perc.	95% perc.	IQ range	Missing obs.
DL_HSI	-0.084924	0.081638	0.061999	0
DL_NSI	-0.097227	0.090003	0.062386	0

1.1.9 Quarterly Frequency – Levels

	Mean	Median	Minimum	Maximum
HSI	19539	20574	12127	28053
NSI	12340	11495	7924.7	17692
	Std. Dev.	C.V.	Skewness	Ex. kurtosis
HSI	3910.3	0.20013	-0.32115	-0.79826
NSI	2920.4	0.23665	0.31199	-1.2982
	5% perc.	95% perc.	IQ range	Missing obs.
HSI	12848	24838	6823.7	0
NSI	8615.8	17260	5289.4	0

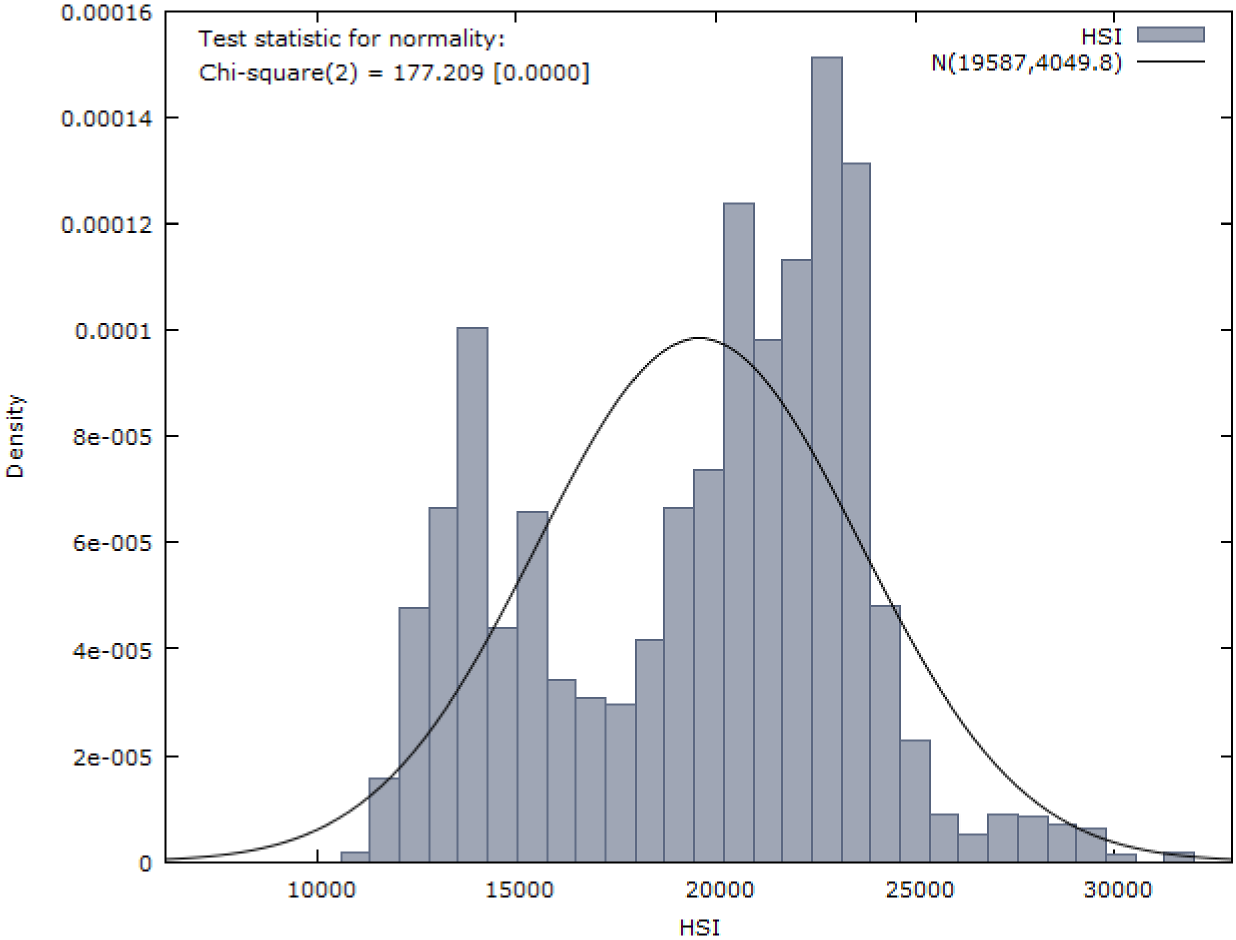
1.1.10 Quarterly Frequency – First Differences of Logarithms



	Mean	Median	Minimum	Maximum
DL_HSI	0.0059253	0.0082184	-0.12298	0.15642
DL_NSI	0.0051539	0.0096818	-0.10412	0.089196
	Std. Dev.	C.V.	Skewness	Ex.kurtosis
DL_HSI	0.048174	8.1303	-0.085815	1.7432
DL_NSI	0.04743	9.2026	-0.32964	-0.50979
	5% perc.	95% perc.	IQ range	Missing obs.
DL_HSI	-0.091311	0.068515	0.053875	0
DL_NSI	-0.085333	0.07651	0.071427	0

1.2 Frequency Distributions

1.2.1 Daily Frequency HSI

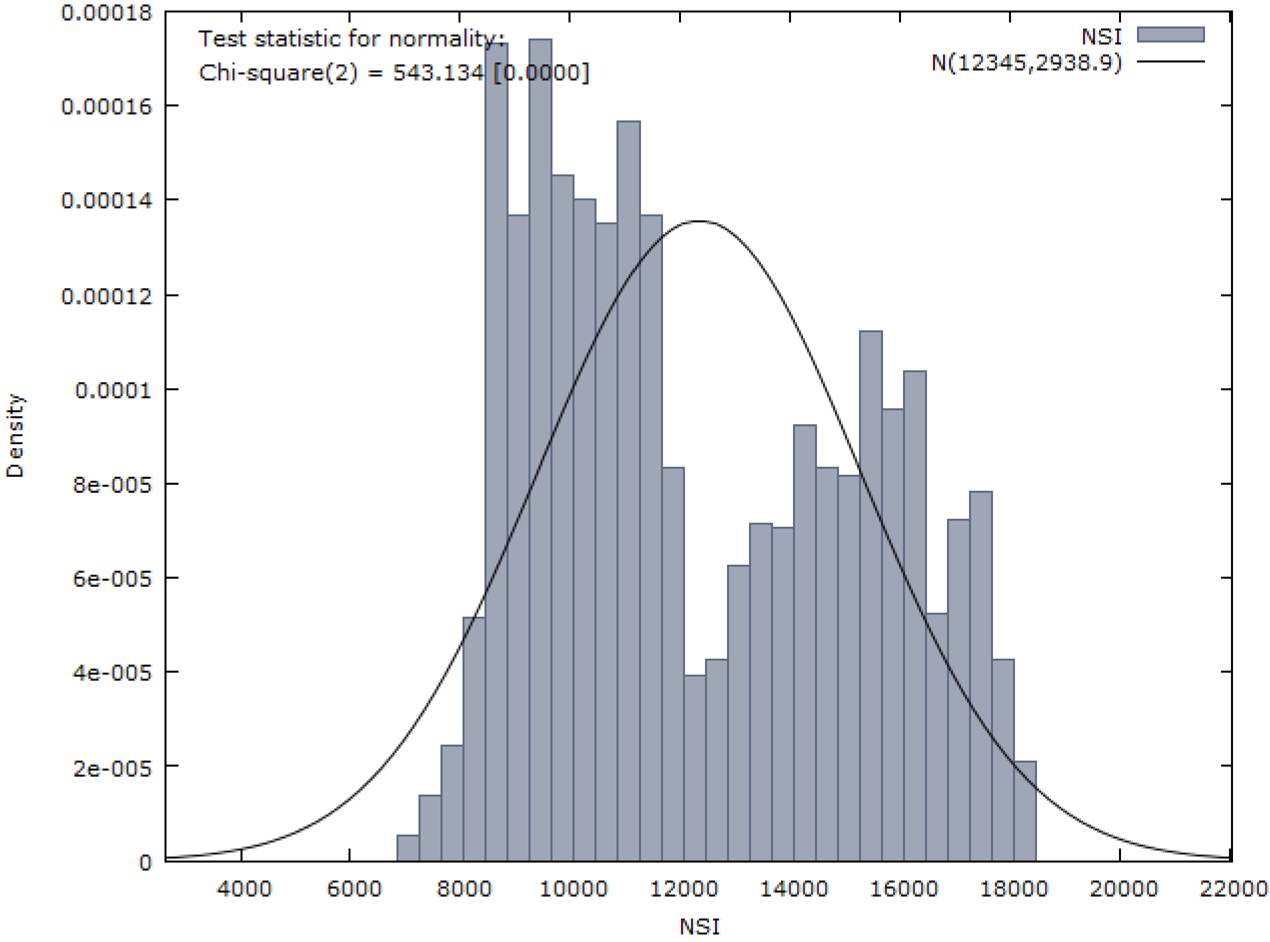


Frequency Distribution for HSI: Obs 1-2870
Number of Bins = 29, Mean = 19586.9, s.d. = 4049.76

Interval	Mid	Freq.	Rel. %	Cum. %	
<11337	10968	4	0.14%	0.14%	
11337-12075	11706	33	1.15%	1.29%	
12075-12813	12444	101	3.52%	4.81%	*
12813-13552	13182	141	4.91%	9.72%	*
13552-14290	13921	213	7.42%	17.14%	**
14290-15028	14659	93	3.24%	20.38%	*
15028-15766	15397	139	4.84%	25.23%	*
15766-16504	16135	72	2.51%	27.74%	
16504-17243	16874	65	2.26%	30.00%	
17243-17981	17612	63	2.20%	32.20%	
17981-18719	18350	88	3.07%	35.26%	*
18719-19457	19088	141	4.91%	40.17%	*
19457-20196	19826	156	5.44%	45.61%	*
20196-20934	20565	262	9.13%	54.74%	***
20934-21672	21303	208	7.25%	61.99%	**
21672-22410	22041	240	8.36%	70.35%	***
22410-23149	22779	321	11.18%	81.53%	****
23149-23887	23518	278	9.69%	91.22%	***
23887-24625	24256	102	3.55%	94.77%	*
24625-25363	24994	48	1.67%	96.45%	
25363-26101	25732	19	0.66%	97.11%	
26101-26840	26471	11	0.38%	97.49%	
26840-27578	27209	19	0.66%	98.15%	
27578-28316	27947	18	0.63%	98.78%	
28316-29054	28685	15	0.52%	99.30%	
29054-29793	29424	13	0.45%	99.76%	
29793-30531	30162	3	0.10%	99.86%	
30531-31269	30900	0	0.00%	99.86%	
>=31269	31638	4	0.14%	100.00%	

Test for null hypothesis of normal distribution:
χ^2 (2) = 177.209 with p-value 0.00000

1.2.2 Daily Frequency NSI

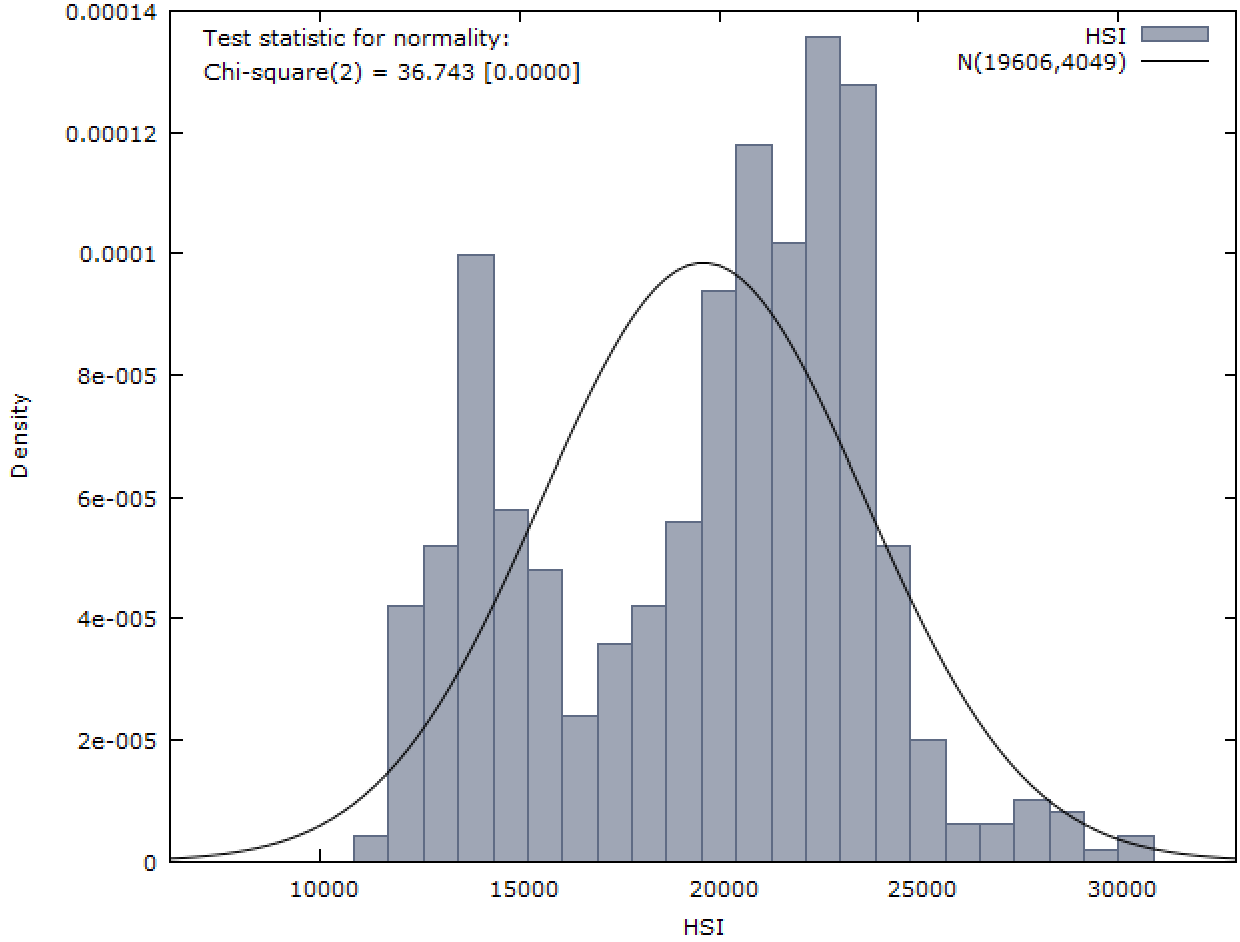


Frequency Distribution for NSI: Obs 1-2870
Number of Bins = 29, Mean = 12344.9, s.d. = 2938.91

Interval	Mid	Freq.	Rel. %	Cum. %	
<7255.1	7055	6	0.21%	0.21%	
7255.1-7655.4	7455.2	16	0.56%	0.77%	
7655.4-8055.6	7855.5	28	0.98%	1.74%	
8055.6-8455.9	8255.7	59	2.06%	3.80%	
8455.9-8856.1	8656	199	6.93%	10.73%	**
8856.1-9256.4	9056.2	157	5.47%	16.20%	*
9256.4-9656.6	9456.5	200	6.97%	23.17%	**
9656.6-10057	9856.7	167	5.82%	28.99%	**
10057-10457	10257	161	5.61%	34.60%	**
10457-10857	10657	155	5.40%	40.00%	*
10857-11258	11057	180	6.27%	46.27%	**
11258-11658	11458	157	5.47%	51.74%	*
11658-12058	11858	96	3.34%	55.09%	*
12058-12458	12258	45	1.57%	56.66%	
12458-12859	12658	49	1.71%	58.36%	
12859-13259	13059	72	2.51%	60.87%	
13259-13659	13459	82	2.86%	63.73%	*
13659-14059	13859	81	2.82%	66.55%	*
14059-14460	14259	106	3.69%	70.24%	*
14460-14860	14660	96	3.34%	73.59%	*
14860-15260	15060	94	3.28%	76.86%	*
15260-15660	15460	129	4.49%	81.36%	*
15660-16061	15860	110	3.83%	85.19%	*
16061-16461	16261	119	4.15%	89.34%	*
16461-16861	16661	60	2.09%	91.43%	
16861-17261	17061	83	2.89%	94.32%	*
17261-17662	17461	90	3.14%	97.46%	*
17662-18062	17862	49	1.71%	99.16%	
>=18062	18262	24	0.84%	100.00%	

Test for null hypothesis of normal distribution:
χ^2 (2) = 543.134 with p-value 0.00000

1.2.3 Weekly Frequency HSI

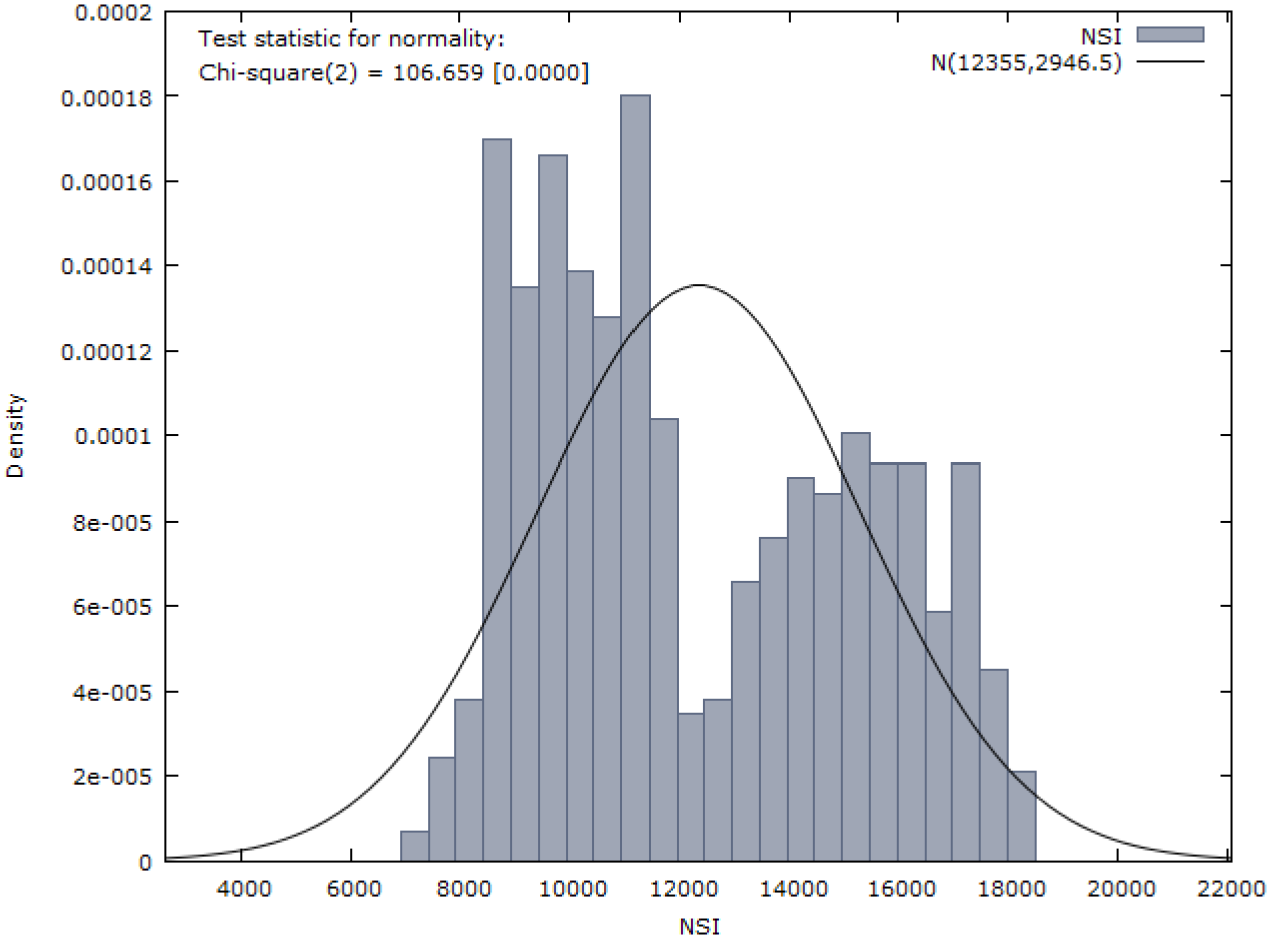


Frequency Distribution for NSI: Obs 1-574
Number of Bins = 23, Mean = 19606.5, s.d. = 4048.98

Interval	Mid	Freq.	Rel. %	Cum. %	
<11713	11277	2	0.35%	0.35%	
11713-12585	12149	21	3.66%	4.01%	*
12585-13458	13022	26	4.53%	8.54%	*
13458-14330	13894	50	8.71%	17.25%	***
14330-15202	14766	29	5.05%	22.30%	*
15202-16075	15639	24	4.18%	26.48%	*
16075-16947	16511	12	2.09%	28.57%	
16947-17819	17383	18	3.14%	31.71%	*
17819-18692	18256	21	3.66%	35.37%	*
18692-19564	19128	28	4.88%	40.24%	*
19564-20436	20000	47	8.19%	48.43%	**
20436-21309	20873	59	10.28%	58.71%	***
21309-22181	21745	51	8.89%	67.60%	***
22181-23053	22617	68	11.85%	79.44%	****
23053-23926	23490	64	11.15%	90.59%	****
23926-24798	24362	26	4.53%	95.12%	*
24798-25670	25234	10	1.74%	96.86%	
25670-26543	26107	3	0.52%	97.39%	
26543-27415	26979	3	0.52%	97.91%	
27415-28287	27851	5	0.87%	98.78%	
28287-29160	28724	4	0.70%	99.48%	
29160-30032	29596	1	0.17%	99.65%	
>=30032	30468	2	0.35%	100.00%	

Test for null hypothesis of normal distribution:
χ^2 (2) = 36.743 with p-value 0.00000

1.2.4 Weekly Frequency NSI

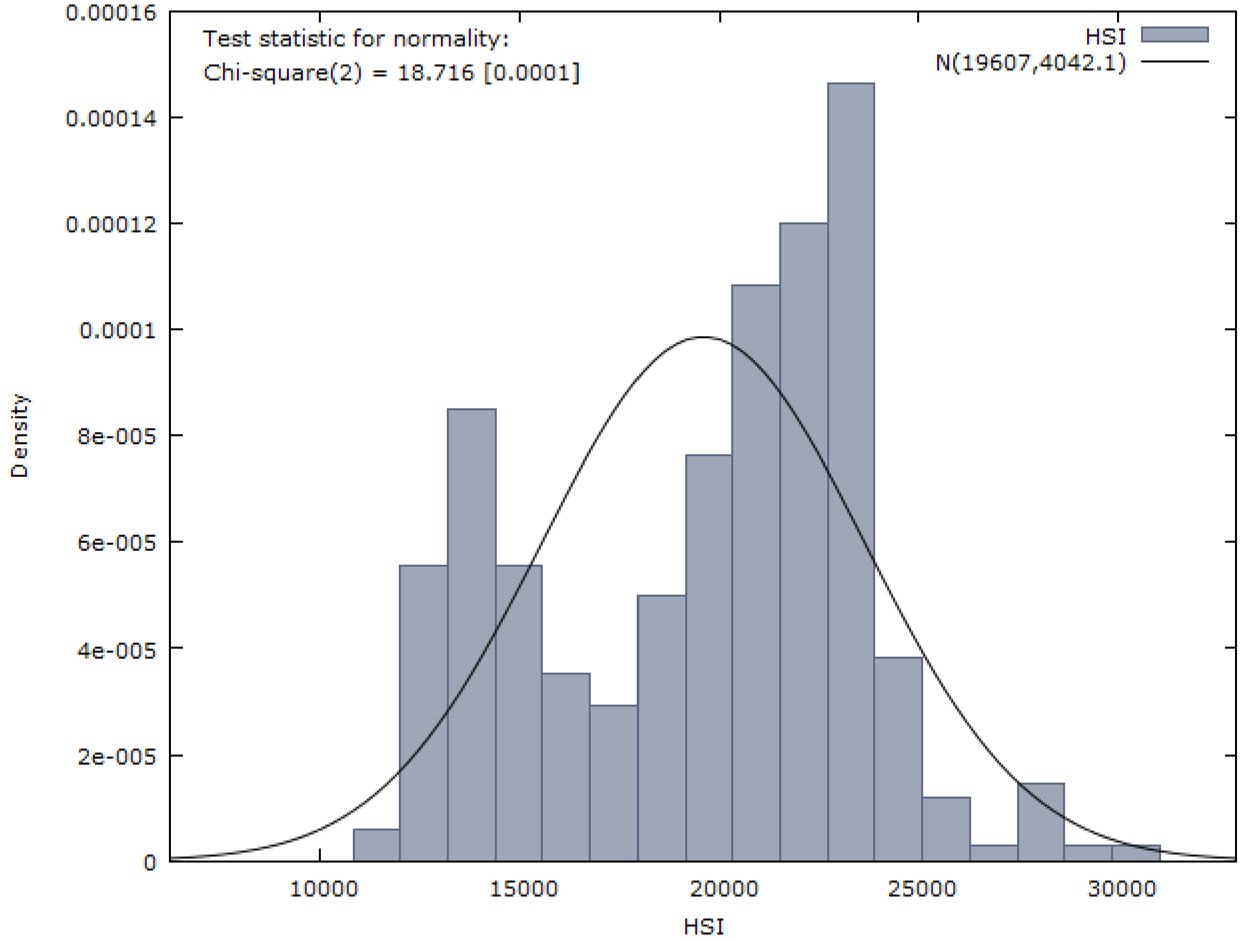


Frequency Distribution for NSI: Obs 1-574
Number of Bins = 23, Mean = 12355.2, s.d. = 2946.47

Interval	Mid	Freq.	Rel. %	Cum. %	
<7424.6	7173.1	2	0.35%	0.35%	
7424.6-7927.6	7676.1	7	1.22%	1.57%	
7927.6-8430.6	8179.1	11	1.92%	3.48%	
8430.6-8933.6	8682.1	49	8.54%	12.02%	***
8933.6-9436.6	9185.1	39	6.79%	18.82%	**
9436.6-9939.6	9688.1	48	8.36%	27.18%	***
9939.6-10443	10191	40	6.97%	34.15%	**
10443-10946	10694	37	6.45%	40.59%	**
10946-11449	11197	52	9.06%	49.65%	***
11449-11952	11700	30	5.23%	54.88%	*
11952-12455	12203	10	1.74%	56.62%	
12455-12958	12706	11	1.92%	58.54%	
12958-13461	13209	19	3.31%	61.85%	*
13461-13964	13712	22	3.83%	65.68%	*
13964-14467	14215	26	4.53%	70.21%	*
14467-14969	14718	25	4.36%	74.56%	*
14969-15472	15221	29	5.05%	79.62%	*
15472-15975	15724	27	4.70%	84.32%	*
15975-16478	16227	27	4.70%	89.02%	*
16478-16981	16730	17	2.96%	91.99%	*
16981-17484	17233	27	4.70%	96.69%	*
17484-17987	17736	13	2.26%	98.95%	
>=17987	18239	6	1.05%	100.00%	

Test for null hypothesis of normal distribution:
χ^2 (2) = 106.659 with p-value 0.00000

1.2.5 Fortnightly Frequency HSI

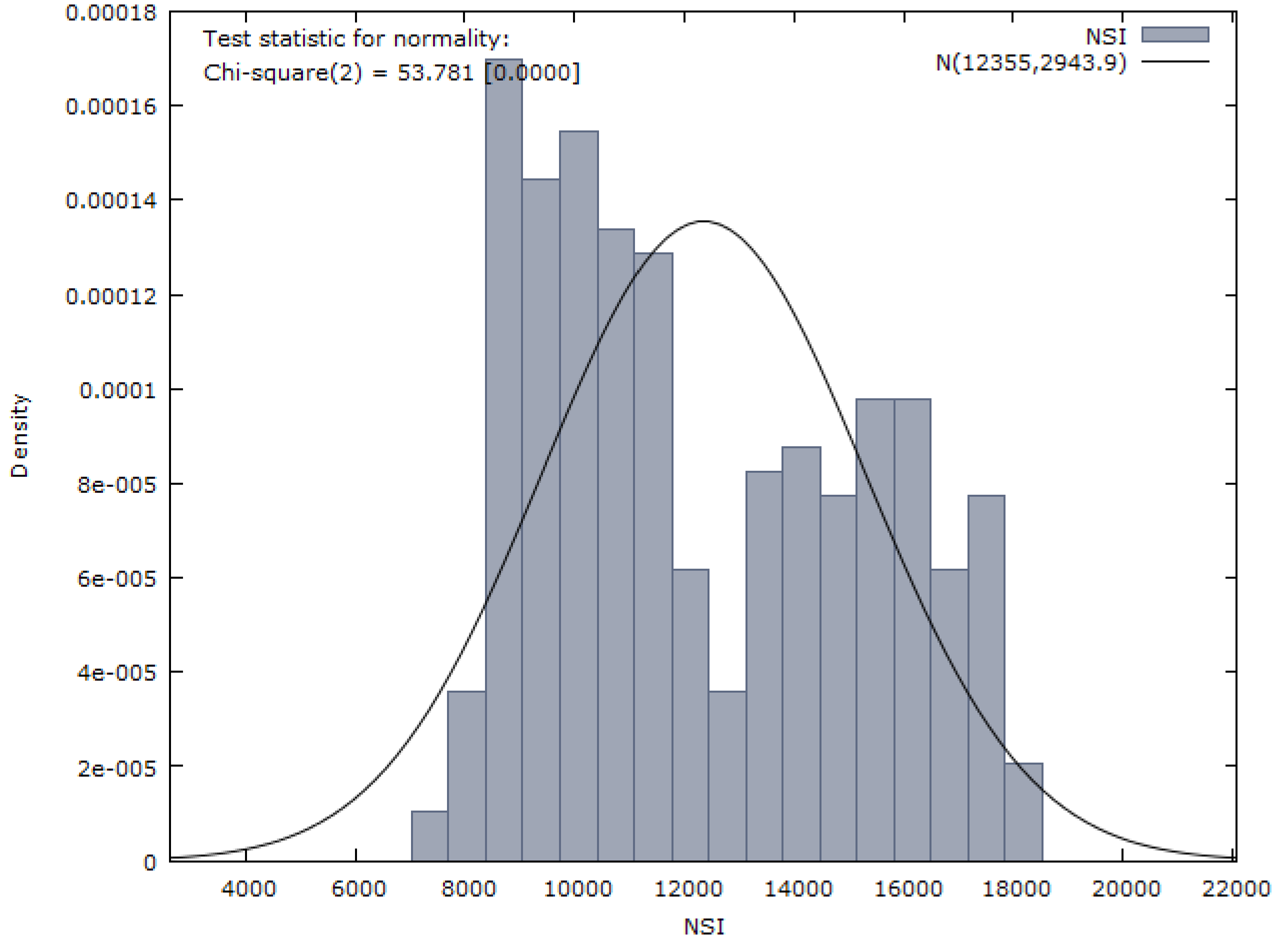


Frequency Distribution for NSI: Obs 1-287
Number of Bins = 17, Mean = 19606.5, s.d. = 4042.1

Interval	Mid	Freq.	Rel. %	Cum. %	
<=12021	11426	2	0.70%	0.70%	
12021-13209	12615	19	6.62%	7.32%	**
13209-14397	13803	29	10.10%	17.42%	***
14397-15585	14991	19	6.62%	24.04%	**
15585-16733	16179	12	4.18%	28.22%	*
16733-17961	17367	10	3.48%	31.71%	*
17961-19149	18555	17	5.92%	37.63%	**
19149-20338	19743	26	9.06%	46.69%	***
20338-21526	20932	37	12.89%	59.58%	****
21526-22714	22120	41	14.29%	73.87%	*****
22714-23902	23308	50	17.42%	91.29%	******
23902-25090	24496	13	4.53%	95.82%	*
25090-26278	25684	4	1.39%	97.21%	
26278-27466	26872	1	0.35%	97.56%	
27466-28655	28060	5	1.74%	99.30%	
28655-29843	29249	1	0.35%	99.65%	
>= 29843	30437	1	0.35%	100.00%	

Test for null hypothesis of normal distribution:
χ^2 (2) = 18.716 with p-value 0.00009

1.2.6 Fortnightly Frequency NSI

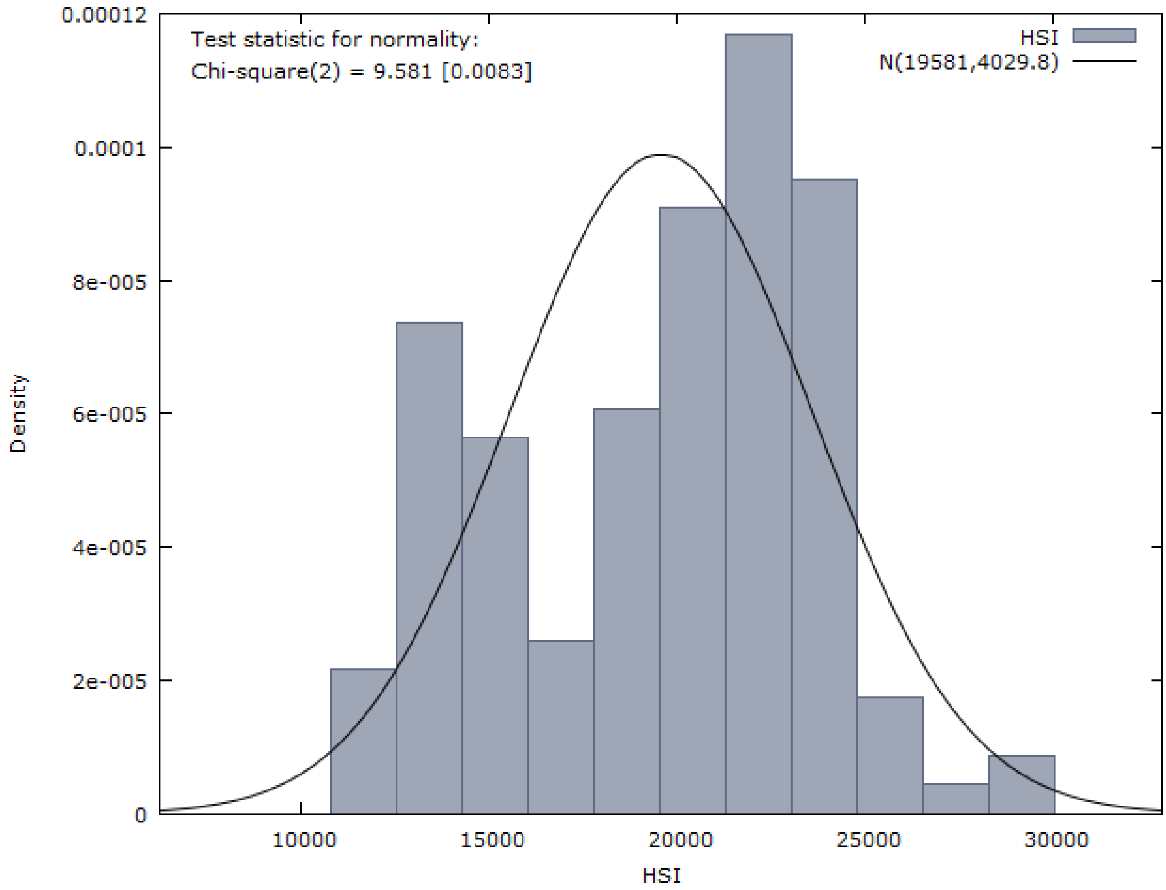


Frequency Distribution for NSI: Obs 1-287
Number of Bins = 17, Mean = 12355.2, s.d. = 2943.9

Interval	Mid	Freq.	Rel. %	Cum. %	
<7709	7370.8	2	0.70%	0.70%	
7708.9-8385.1	8047.0	7	2.44%	3.14%	
8385.1-9061.3	8723.2	33	11.49%	14.63%	****
9061.3-9737.5	9399.4	28	9.76%	24.39%	***
9737.5-10414	10076.0	30	10.45%	34.84%	***
10414.1-11090	10752.0	26	9.06%	43.90%	***
11090.1-11766	11428.0	25	8.71%	52.61%	***
11766.1-12442	12104.0	12	4.18%	56.79%	*
12442.1-13118	12780.0	7	2.44%	59.23%	
13118.1-13795	13457.0	16	5.57%	64.81%	**
13795.1-14471	14133.0	17	5.92%	70.73%	**
14471.1-15147	14809.0	15	5.23%	75.96%	*
15147.1-15823	15485.0	19	6.62%	82.58%	**
15823.1-16499	16161.0	19	6.62%	89.20%	**
16499.1-17176	16838.0	12	4.18%	93.38%	*
17176.1-17852	17514.0	15	5.23%	98.61%	*
>=17852	18190.0	4	1.39%	100.00%	

Test for null hypothesis of normal distribution:
χ^2 (2) = 53.781 with p-value 0.00009

1.2.7 Monthly Frequency HSI

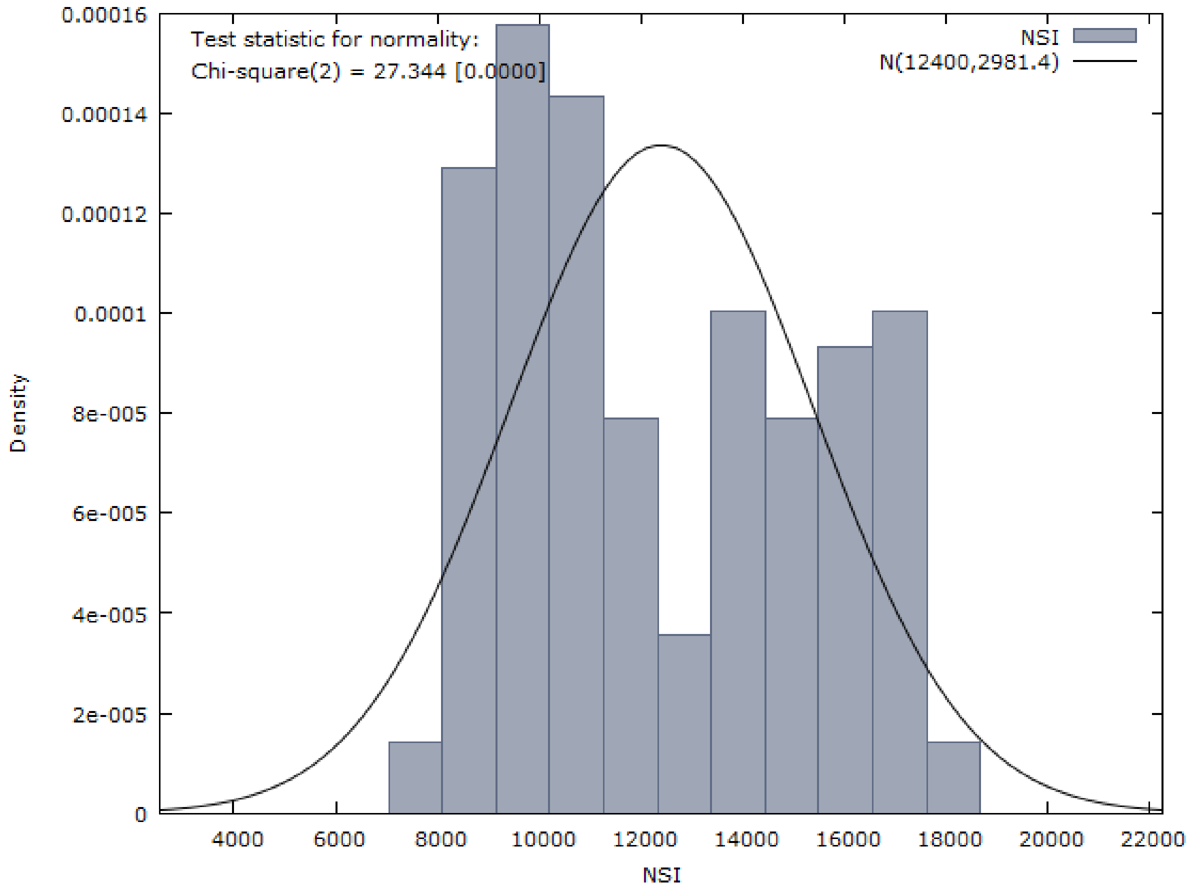


Frequency Distribution for NSI: Obs 1-132
Number of Bins = 11, Mean = 19581.3, s.d. = 4029.81

Interval	Mid	Freq.	Rel. %	Cum. %
< 12536	11661	5	3.79	3.79%
12536-14285	13410	17	12.88	16.67%
14285-16034	15160	13	9.85	26.52%
16034-17783	16909	6	4.55	31.06%
17783-19532	18658	14	10.61	41.67%
19532-21282	20407	21	15.91	57.58%
21282-23031	22156	27	20.45	78.03%
23031-24780	23905	22	16.67	94.70%
24780-26529	25654	4	3.03	97.73%
26529-28278	27403	1	0.76	98.48%
>= 28278	29153	2	1.52	100.00%

Test for null hypothesis of normal distribution:
χ^2 (2) = 9.581 with p-value 0.00000

1.2.8 Monthly Frequency NSI

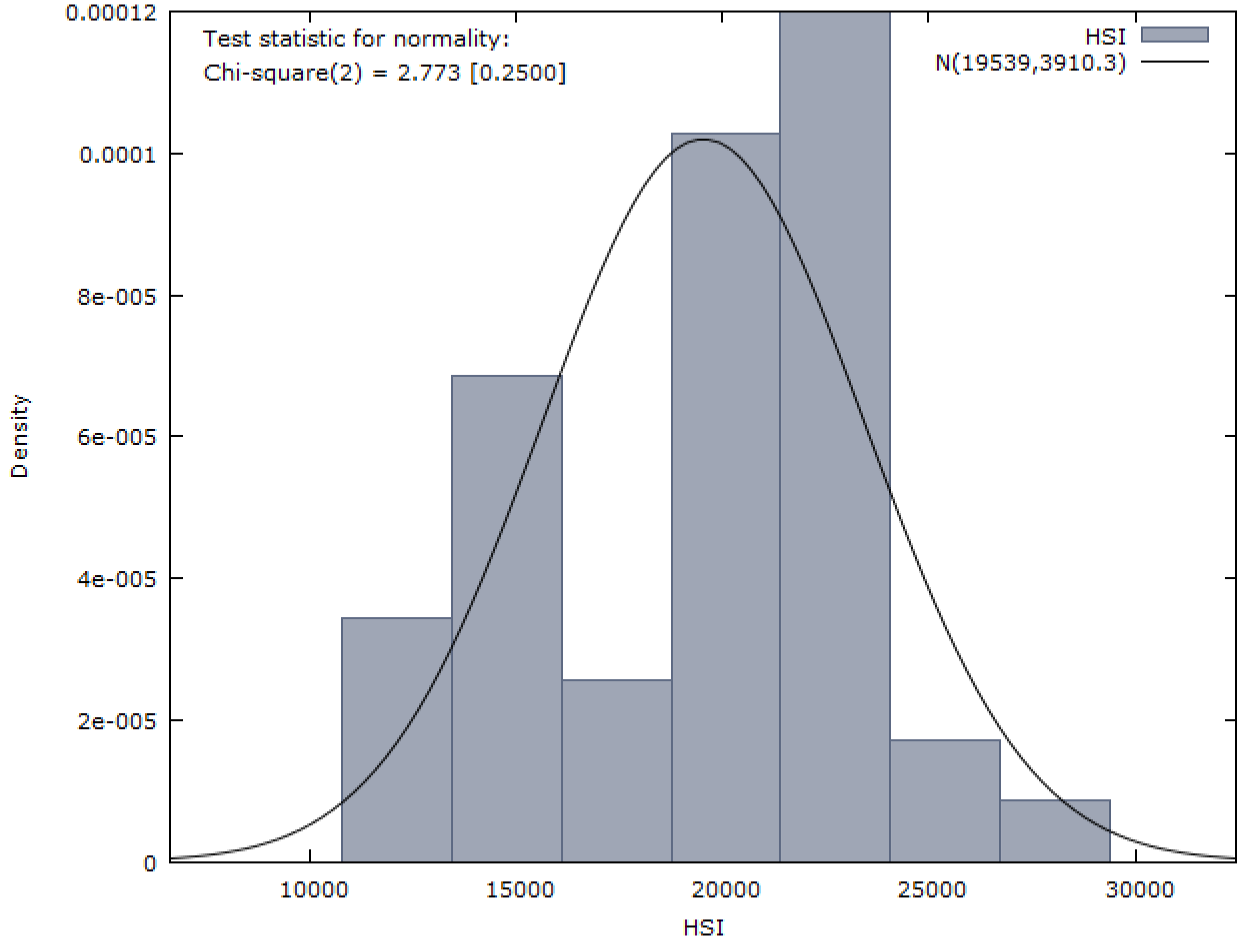


Frequency Distribution for NSI: Obs 1-132
Number of Bins = 11, Mean = 12400.5, s.d. = 2981.44

Interval	Mid	Freq.	Rel. %	Cum. %
< 8096.9	7568.4	2	1.52	1.52%
8096.9-9153.9	8625.4	18	13.64	15.15%
9153.9-10211	9682.4	22	16.67	31.82%
10211-11268	10739	20	15.15	46.97%
11268-12325	11796	11	8.33	55.30%
12325-13382	12853	5	3.79	59.09%
13382-14439	13910	14	10.61	69.7%
14439-15496	14967	11	8.33	78.03%
15496-16553	16024	13	9.85	87.88%
16553-17610	17081	14	10.61	98.48%
>= 17610	18138	2	1.52	100.00%

Test for null hypothesis of normal distribution:
χ^2 (2) = 27.344 with p-value 0.00000

1.2.9 Quarterly Frequency HSI

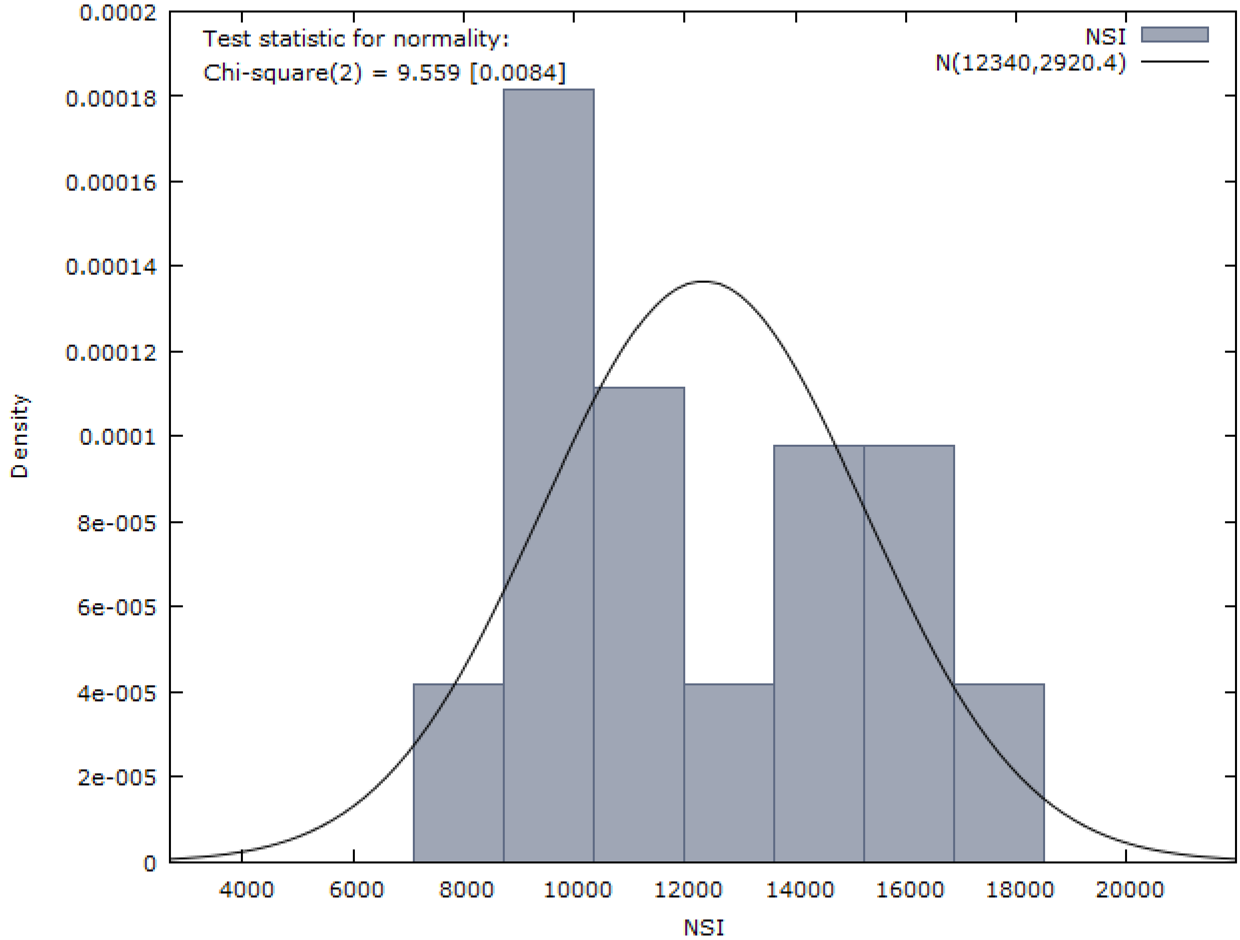


Frequency Distribution for NSI: Obs 1-44
Number of Bins = 7, Mean = 19539.3, s.d. = 3910.33

Interval	Mid	Freq.	Rel. %	Cum. %	
<13455	12127	4	9.09%	9.09%	***
13455-16109	14782	8	18.18%	27.27%	******
16109-18763	17436	3	6.82%	34.09%	**
18763-21417	20090	12	27.27%	61.36%	*********
21417-24071	22744	14	31.82%	93.18%	***********
24071-26726	25398	2	4.55%	97.73%	*
>=26726	28053	1	2.27%	100.00%	

Test for null hypothesis of normal distribution:
χ^2 (2) = 2.773 with p-value 0.24997

1.2.10 Quarterly Frequency NSI



Frequency Distribution for NSI: Obs 1-44
Number of Bins = 7, Mean = 12340.2, s.d. = 2920.36

Interval	Mid	Freq.	Rel. %	Cum. %	
<8738.6	7924.7	3	6.82%	6.82%	**
8738.6-10367	9552.6	13	29.55%	36.36%	**********
10367-11995	11181	8	18.18%	54.55%	******
11995-13622	12808	3	6.82%	61.36%	**
13622-15250	14436	7	15.91%	77.27%	*****
15250-16878	16064	7	15.91%	93.18%	*****
>=16878	17692	3	6.82%	100.00%	**

Test for null hypothesis of normal distribution:
χ^2 (2) = 9.559 with p-value 0.00840

1.3 Jarque-Bera Statistics

Market	Frequency	JB-Statistic	p-value
HSI	Daily	99.924	2.0037E-22
HSI	Weekly	20.932	2.8499E-05
HSI	Fortnightly	10.819	4.4745E-03
HSI	Monthly	5.589	6.1140E-02
HSI	Quarterly	1.925	3.8202E-01
NSI	Daily	224.212	2.0055E-49
NSI	Weekly	44.515	2.1567E-10
NSI	Fortnightly	22.446	1.3663E-05
NSI	Monthly	10.693	4.7649E-03
NSI	Quarterly	3.803	1.4931E-01

1.4 Augmented Dickey Fuller Tests

1.4.1 ADF Tests – Daily Frequency HSI

ADF test for HSI including 6 lags based on AIC
n=2863
Unit-root null hypothesis: a = 1

Test with constant
Model: (1-L)y = b0 + (a-1)*y(-1) + ... + e
1st-order autocorrelation coeff. for e: 0.001
Lagged differences: F(6, 2855) = 1.174 [0.3170]
Estimated value of (a - 1): -0.002637
Test statistic: tau_c(1) = -1.95295
Asymptotic p-value 0.3081

With constant and trend
Model: (1-L)y = b0 + b1*t + (a-1)*y(-1) + ... + e
1st-order autocorrelation coeff. for e: 0.001
Lagged differences: F(6, 2854) = 1.094 [0.3634]
Estimated value of (a - 1): -0.00425988
Test statistic: tau_ct(1) = -2.36249
Asymptotic p-value 0.3994

1.4.2 ADF Tests – Daily Frequency NSI

ADF test for NSI including 3 lags based on AIC
n=2866
Unit-root null hypothesis: a = 1

Test with constant
Model: (1-L)y = b0 + (a-1)*y(-1) + ... + e
1st-order autocorrelation coeff. for e: -0.000
Lagged differences: F(3, 2861) = 1.206 [0.3061]
Estimated value of (a - 1): -0.00117507
Test statistic: tau_c(1) = -1.0546
Asymptotic p-value 0.7356

With constant and trend
Model: (1-L)y = b0 + b1*t + (a-1)*y(-1) + ... + e
1st-order autocorrelation coeff. for e: -0.000
Lagged differences: F(3, 2860) = 1.224 [0.2995]
Estimated value of (a - 1): -0.00109674
Test statistic: tau_ct(1) = -0.976923
Asymptotic p-value 0.9455

1.4.3 ADF Tests – Weekly Frequency HSI

ADF test for HSI including 1 lag based on AIC
n=572
Unit-root null hypothesis: a = 1

Test with constant
Model: (1-L)y = b0 + (a-1)*y(-1) + ... + e
1st-order autocorrelation coeff. for e: 0.000
Estimated value of (a - 1): -0.0122939
Test statistic: tau_c(1) = -1.99523
Asymptotic p-value 0.2892

With constant and trend
Model: (1-L)y = b0 + b1*t + (a-1)*y(-1) + ... + e
1st-order autocorrelation coeff. for e: -0.000
Estimated value of (a - 1): -0.0197
Test statistic: tau_ct(1) = -2.39874
Asymptotic p-value 0.3801

1.4.4 ADF Tests – Weekly Frequency NSI

ADF test for NSI including 7 lags based on AIC
n=586
Unit-root null hypothesis: a = 1

Test with constant
Model: (1-L)y = b0 + (a-1)*y(-1) + ... + e
1st-order autocorrelation coeff. for e: 0.001
Lagged differences: F(7, 557) = 1.125 [0.3459]
Estimated value of (a - 1): -0.00508848
Test statistic: tau_c(1) = -0.94619
Asymptotic p-value 0.774

With constant and trend
Model: (1-L)y = b0 + b1*t + (a-1)*y(-1) + ... + e
1st-order autocorrelation coeff. for e: 0.001
Lagged differences: F(7, 556) = 1.127 [0.3441]
Estimated value of (a - 1): -0.00455145
Test statistic: tau_ct(1) = -0.83554
Asymptotic p-value 0.9611

1.4.5 ADF Tests – Fortnightly Frequency HSI

ADF test for HSI including 1 lag based on AIC
n=285
Unit-root null hypothesis: a = 1

Test with constant
Model: (1-L)y = b0 + (a-1)*y(-1) + ... + e
1st-order autocorrelation coeff. for e: 0.001
Estimated value of (a - 1): -0.0221666
Test statistic: tau_c(1) = -2.08933
Asymptotic p-value 0.2491

With constant and trend
Model: (1-L)y = b0 + b1*t + (a-1)*y(-1) + ... + e
1st-order autocorrelation coeff. for e: -0.002
Estimated value of (a - 1): -0.0364838
Test statistic: tau_ct(1) = -2.58116
Asymptotic p-value 0.289

1.4.6 ADF Tests – Fortnightly Frequency NSI

ADF test for NSI including 2 lags based on AIC
n=284
Unit-root null hypothesis: a = 1

Test with constant
Model: (1-L)y = b0 + (a-1)*y(-1) + ... + e
1st-order autocorrelation coeff. for e: 0.007
Lagged differences: F(2, 280) = 9.491 [0.0001]
Estimated value of (a - 1): -0.00875712
Test statistic: tau_c(1) = -0.948799
Asymptotic p-value 0.7731

With constant and trend
Model: (1-L)y = b0 + b1*t + (a-1)*y(-1) + ... + e
1st-order autocorrelation coeff. for e: 0.007
Lagged differences: F(2, 279) = 9.397 [0.0001]
Estimated value of (a - 1): -0.0079808
Test statistic: tau_ct(1) = -0.854247
Asymptotic p-value 0.9593

1.4.7 ADF Tests – Monthly Frequency HSI

ADF test for HSI including 2 lags based on AIC

n=129

Unit-root null hypothesis: a = 1

Test with constant

Model: (1-L)y = b0 + (a-1)*y(-1) + ... + e

1st-order autocorrelation coeff. for e: -0.003

Lagged differences: F(2, 125) = 7.686 [0.0007]

Estimated value of (a - 1): -0.0519082

Test statistic: tau_c(1) = -2.30311

Asymptotic p-value 0.171

With constant and trend

Model: (1-L)y = b0 + b1*t + (a-1)*y(-1) + ... + e

1st-order autocorrelation coeff. for e: -0.002

Estimated value of (a - 1): -0.0825009

Test statistic: tau_ct(1) = -2.824

Asymptotic p-value 0.1884

1.4.8 ADF Tests – Monthly Frequency NSI

ADF test for NSI including one lag based on AIC

n=130

Unit-root null hypothesis: a = 1

Test with constant

Model: (1-L)y = b0 + (a-1)*y(-1) + ... + e

1st-order autocorrelation coeff. for e: -0.003

Estimated value of (a - 1): -0.0231621

Test statistic: tau_c(1) = -1.14872

Asymptotic p-value 0.6985

With constant and trend

Model: (1-L)y = b0 + b1*t + (a-1)*y(-1) + ... + e

1st-order autocorrelation coeff. for e: -0.003

Estimated value of (a - 1): -0.0217714

Test statistic: tau_ct(1) = -1.06246

Asymptotic p-value 0.9336

1.4.9 ADF Tests – Quarterly Frequency HSI

ADF test for HSI including 1 lag based on AIC
n=42
Unit-root null hypothesis: a = 1

Test with constant
Model: (1-L)y = b0 + (a-1)*y(-1) + ... + e
1st-order autocorrelation coeff. for e: 0.013
Estimated value of (a - 1): -0.22806
Test statistic: tau_c(1) = -2.69597
Asymptotic p-value 0.07466

With constant and trend
Model: (1-L)y = b0 + b1*t + (a-1)*y(-1) + ... + e
1st-order autocorrelation coeff. for e: -0.005
Estimated value of (a - 1): -0.366857
Test statistic: tau_ct(1) = -3.29461
Asymptotic p-value 0.06708

1.4.10 ADF Tests – Quarterly Frequency NSI

ADF test for NSI including 2 lags of based on AIC
n=41
Unit-root null hypothesis: a = 1

Test with constant
Model: (1-L)y = b0 + (a-1)*y(-1) + ... + e
1st-order autocorrelation coeff. for e: 0.049
Lagged differences: F(2, 37) = 4.369 [0.0198]
Estimated value of (a - 1): -0.0815707
Test statistic: tau_c(1) = -1.27395
Asymptotic p-value 0.6439

With constant and trend
Model: (1-L)y = b0 + b1*t + (a-1)*y(-1) + ... + e
1st-order autocorrelation coeff. for e: 0.050
Lagged differences: F(2, 36) = 4.126 [0.0244]
Estimated value of (a - 1): -0.0778593
Test statistic: tau_ct(1) = -1.1495
Asymptotic p-value 0.9192

1.5 Vector Auto-Regression (VAR) Lag Selection

1.5.1 VAR Lag Selection – Daily Frequency HSI

lags	loglik	p(LR)	AIC	BIC	HQC
1	10315.16307		-7.212002*	-7.207835*	-7.210500*
2	10315.17023	0.90475	-7.211308	-7.205058	-7.209054
3	10316.07515	0.17853	-7.211241	-7.202908	-7.208236
4	10316.88435	0.20331	-7.211108	-7.200691	-7.207352
5	10316.88682	0.94395	-7.210410	-7.197910	-7.205903
6	10318.32279	0.09014	-7.210715	-7.196131	-7.205457
7	10319.37710	0.14647	-7.210753	-7.194086	-7.204743
8	10320.28035	0.17893	-7.210686	-7.191935	-7.203925
9	10321.20767	0.17324	-7.210635	-7.189801	-7.203122
10	10323.98534	0.01842	-7.211878	-7.18896	-7.203614

1.5.2 VAR Lag Selection – Daily Frequency NSI

lags	loglik	p(LR)	AIC	BIC	HQC
1	10337.80477		-7.23036	-7.226196*	-7.228861*
2	10339.14842	0.10115	-7.23060	-7.22435	-7.22835
3	10341.35046	0.03585	-7.231445*	-7.22311	-7.22844
4	10341.51302	0.56855	-7.23086	-7.22044	-7.22710
5	10341.92393	0.36464	-7.23045	-7.21794	-7.22594
6	10342.55615	0.26081	-7.23019	-7.21560	-7.22493
7	10342.58927	0.79688	-7.22951	-7.21284	-7.22350
8	10342.64719	0.73360	-7.22885	-7.21010	-7.22209
9	10342.68597	0.78062	-7.22818	-7.20734	-7.22067
10	10342.82220	0.60168	-7.22758	-7.20465	-7.21931

1.5.3 VAR Lag Selection – Weekly Frequency HSI

lags	loglik	p(LR)	AIC	BIC	HQC
1	1648.24085		-5.796623	-5.781334*	-5.790656*
2	1649.28860	0.14773	-5.796791*	-5.773857	-5.787841
3	1649.48076	0.53531	-5.793946	-5.763368	-5.782014
4	1649.50226	0.83571	-5.790501	-5.752278	-5.775585
5	1649.76145	0.47154	-5.787892	-5.742025	-5.769994

1.5.4 VAR Lag Selection – Weekly Frequency NSI

lags	loglik	p(LR)	AIC	BIC	HQC
1	1655.32059		-5.770752	-5.755566*	-5.764829
2	1658.47785	0.01198	-5.778282	-5.755503	-5.769396
3	1661.21751	0.01924	-5.784354*	-5.753982	-5.772507*
4	1661.23386	0.85649	-5.780921	-5.742955	-5.766111
5	1661.27248	0.78108	-5.777565	-5.732006	-5.759794

1.5.5 VAR Lag Selection – Fortnightly Frequency HSI

lags	loglik	p(LR)	AIC	BIC	HQC
1	769.68453		-5.387260*	-5.361628*	-5.376985*
2	769.70812	0.82806	-5.380408	-5.341961	-5.364995
3	770.45107	0.22285	-5.378604	-5.327341	-5.358054
4	770.50804	0.73570	-5.371986	-5.307907	-5.346299
5	771.28508	0.21253	-5.370422	-5.293527	-5.339597

1.5.6 VAR Lag Selection – Fortnightly Frequency NSI

lags	loglik	p(LR)	AIC	BIC	HQC
1	781.41409		-5.527759	-5.501930*	-5.517402*
2	782.90024	0.0847	-5.531207*	-5.492464	-5.515671
3	783.26497	0.39306	-5.526702	-5.475044	-5.505986
4	783.70625	0.34751	-5.522739	-5.458167	-5.496845
5	783.91272	0.52048	-5.517111	-5.439624	-5.486038

1.5.7 VAR Lag Selection – Monthly Frequency HSI

lags	loglik	p(LR)	AIC	BIC	HQC
1	198.17353		-3.113865*	-3.068845*	-3.095575*
2	198.41252	0.48934	-3.101786	-3.034255	-3.074350
3	199.82573	0.09273	-3.108345	-3.018304	-3.071764
4	199.94935	0.61902	-3.094434	-2.981883	-3.048708
5	200.27123	0.42236	-3.083670	-2.948609	-3.028799

1.5.8 VAR Lag Selection – Monthly Frequency NSI

lags	loglik	p(LR)	AIC	BIC	HQC
1	182.19819		-2.860289*	-2.815268*	-2.841998*
2	182.20726	0.89286	-2.84456	-2.777029	-2.817124
3	183.08911	0.18416	-2.842684	-2.752644	-2.806104
4	183.11302	0.82691	-2.827191	-2.714640	-2.781465
5	184.33959	0.11729	-2.830787	-2.695726	-2.775916

1.5.9 VAR Lag Selection – Quarterly Frequency HSI

lags	loglik	p(LR)	AIC	BIC	HQC
1	62.67879		-3.111733	-3.026422*	-3.081124
2	63.99560	0.10462	-3.127979*	-3.000013	-3.082066*
3	63.99560	0.99957	-3.076697	-2.906076	-3.01548
4	64.27746	0.45276	-3.039870	-2.826593	-2.963348

1.5.10 VAR Lag Selection – Quarterly Frequency NSI

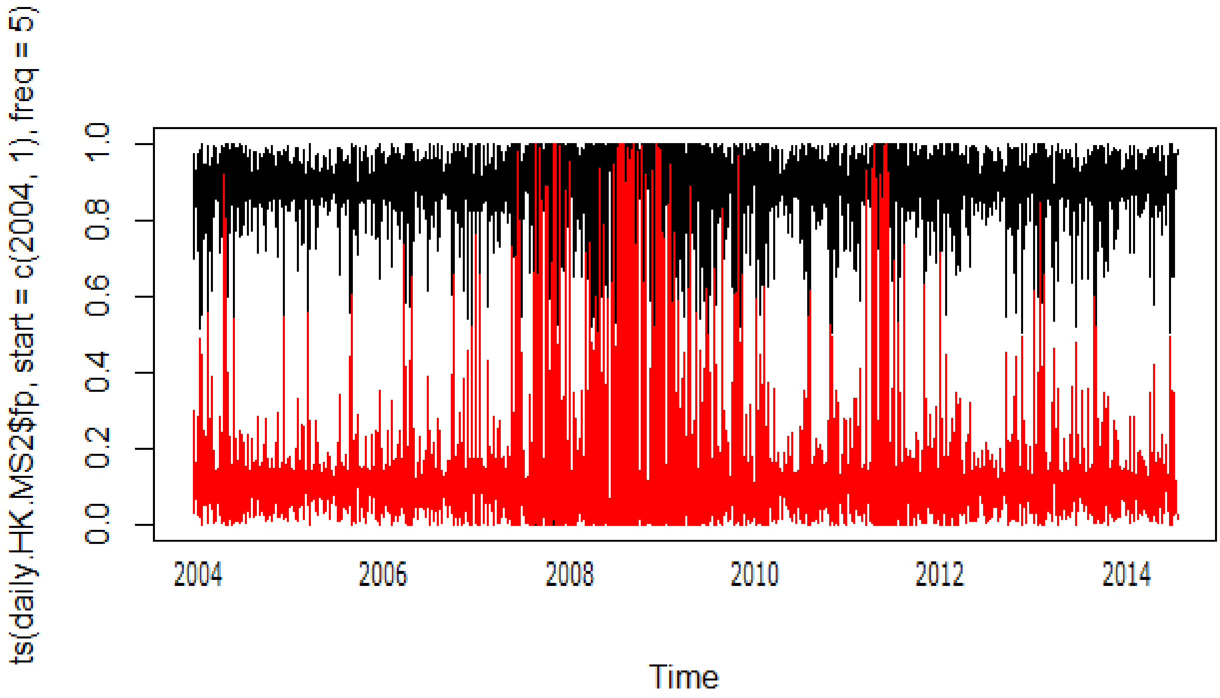
lags	loglik	p(LR)	AIC	BIC	HQC
1	63.40571		-3.149011*	-3.063700*	-3.118402*
2	63.63998	0.49366	-3.109743	-2.981776	-3.06383
3	64.13483	0.31982	-3.083837	-2.913216	-3.02262
4	64.13535	0.97432	-3.032582	-2.819305	-2.95606

1.6 Markov Switching Bayesian VAR Log-Likelihood Ratios

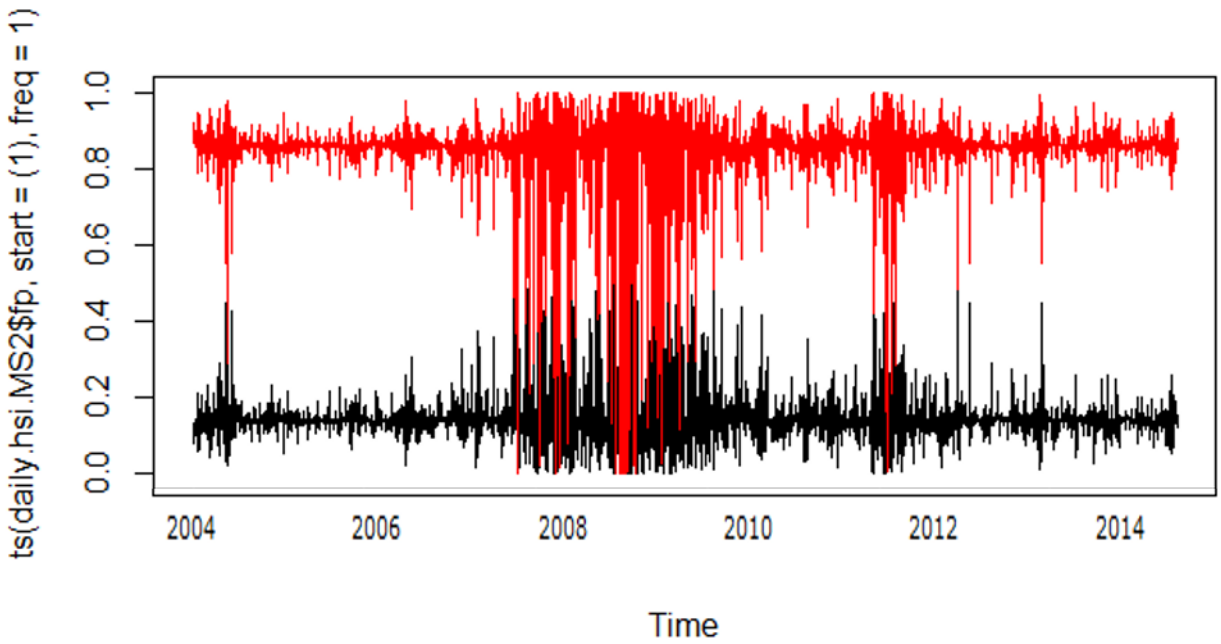
Frequency	Regimes	Lags	HK (iter.)	JAPAN (iter.)
Daily	2	1	10434.65 (7)	10471.08 (10)
Daily	2	2	10470.63 (10)	10519.01 (10)
Daily	2	5	10482.22 (30)	10493.10 (13)
Daily	2	10	10540.48 (5)	10559.29 (15)
Daily	3	1	10731.70 (10)	10610.39 (12)
Daily	3	2	10821.53 (4)	10724.44 (4)
Daily	3	5	10855.86 (5)	10705.85 (5)
Daily	3	10	10795.71 (7)	10724.86 (16)
Weekly	2	1	1680.577 (17)	1699.527 (14)
Weekly	2	2	1711.902 (6)	1712.317 (15)
Weekly	3	1	1733.630 (7)	1718.450 (4)
Weekly	3	2	1733.150 (7)	1728.787 (8)
Fortnightly	2	1	818.0237 (5)	803.2802 (12)
Fortnightly	2	2	821.024 (4)	803.3933 (6)
Fortnightly	3	1	821.1193 (3)	806.5783 (8)
Fortnightly	3	2	819.2826 (6)	807.546 (16)
Monthly	2	1	216.6765	200.8383
Monthly	3	1	217.4721	200.0815
Quarterly	2	1	72.5709 (6)	68.11012 (23)
Quarterly	3	1	70.37282 (8)	62.60133 (4)

1.7 Markov Switching Bayesian VAR Plots

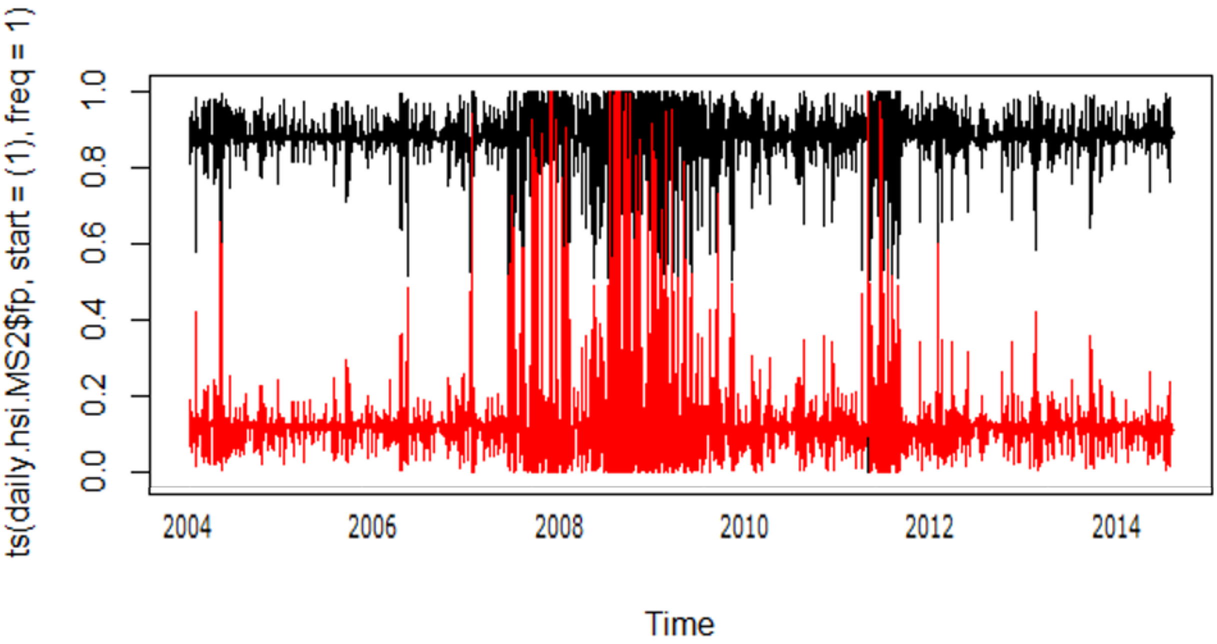
1.7.1 MSBVAR – Daily Frequency HSI: p=1, h=2



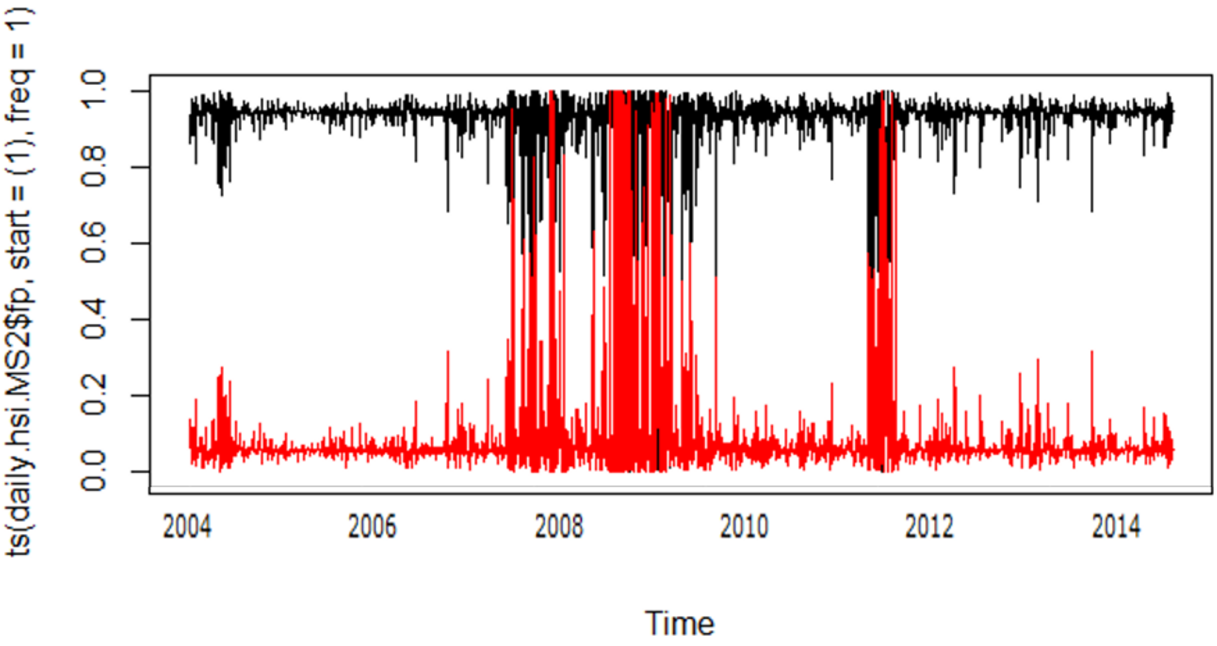
1.7.2 MSBVAR – Daily Frequency HSI: p=2, h=2



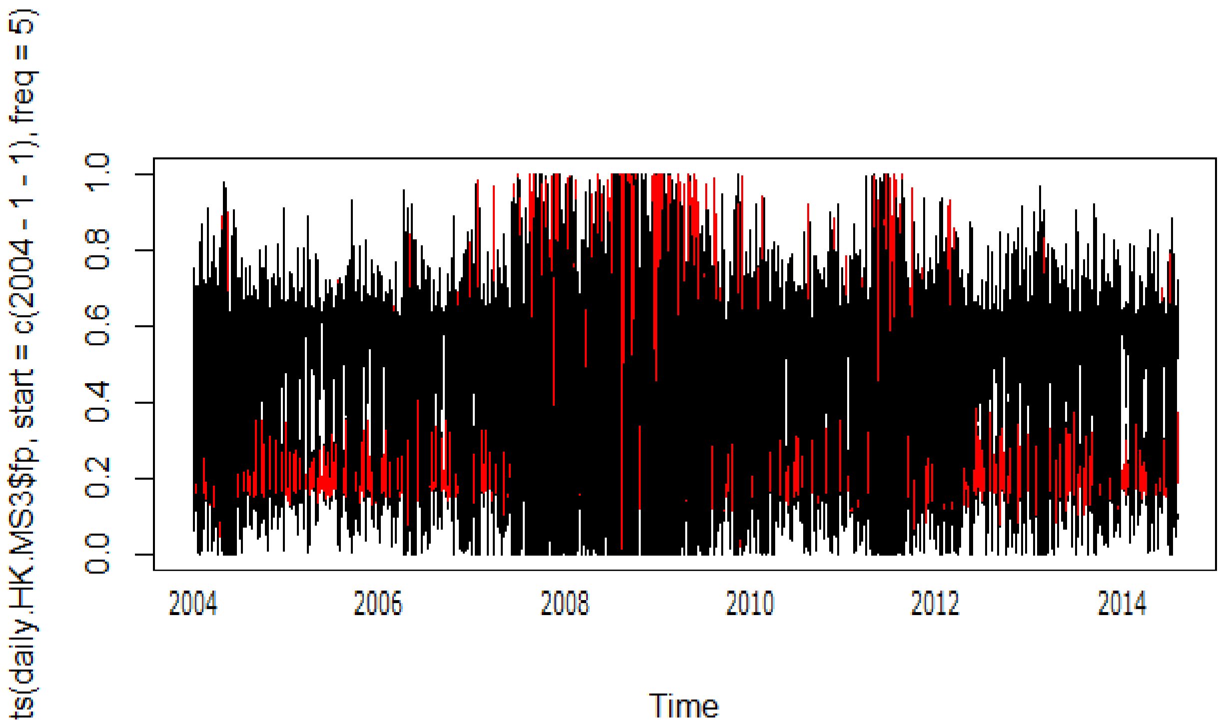
1.7.3 MSBVAR – Daily Frequency HSI: p=5, h=2



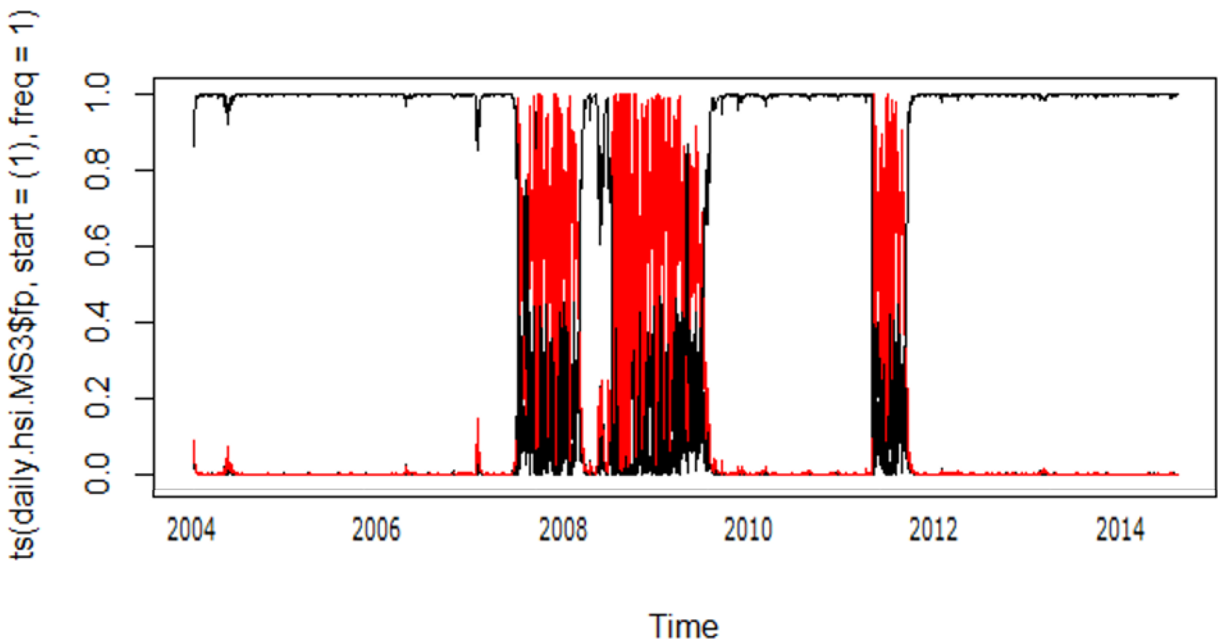
1.7.4 MSBVAR – Daily Frequency HSI: p=10, h=2



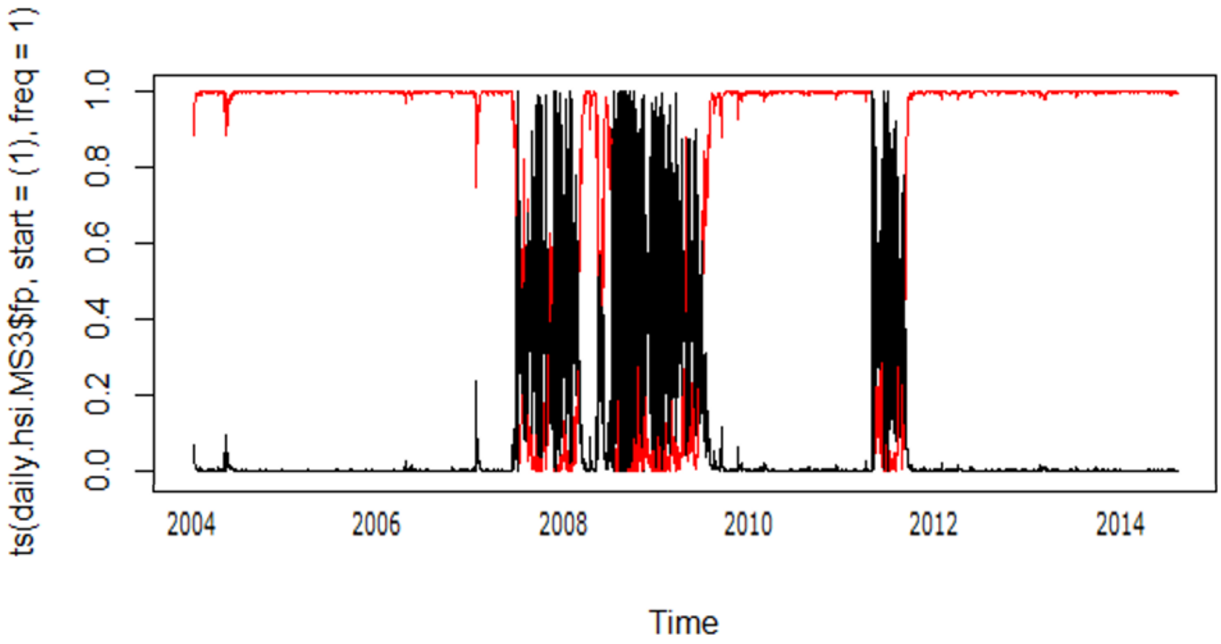
1.7.5 MSBVAR – Daily Frequency HSI: p=1, h=3



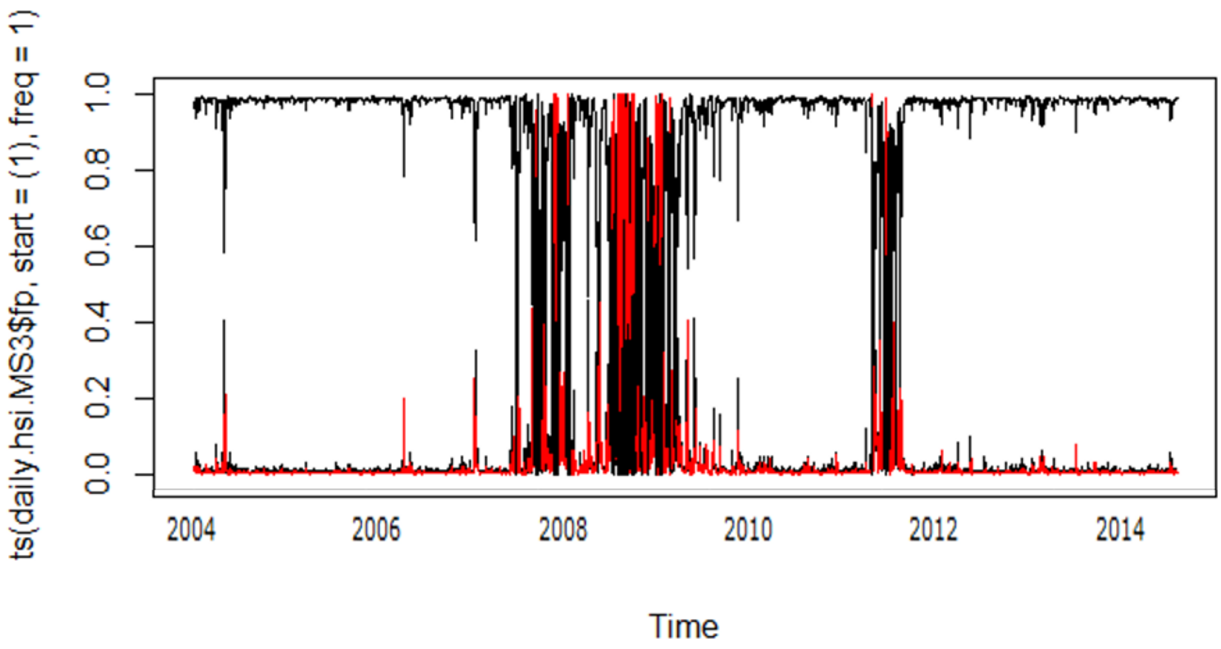
1.7.6 MSBVAR – Daily Frequency HSI: p=2, h=3



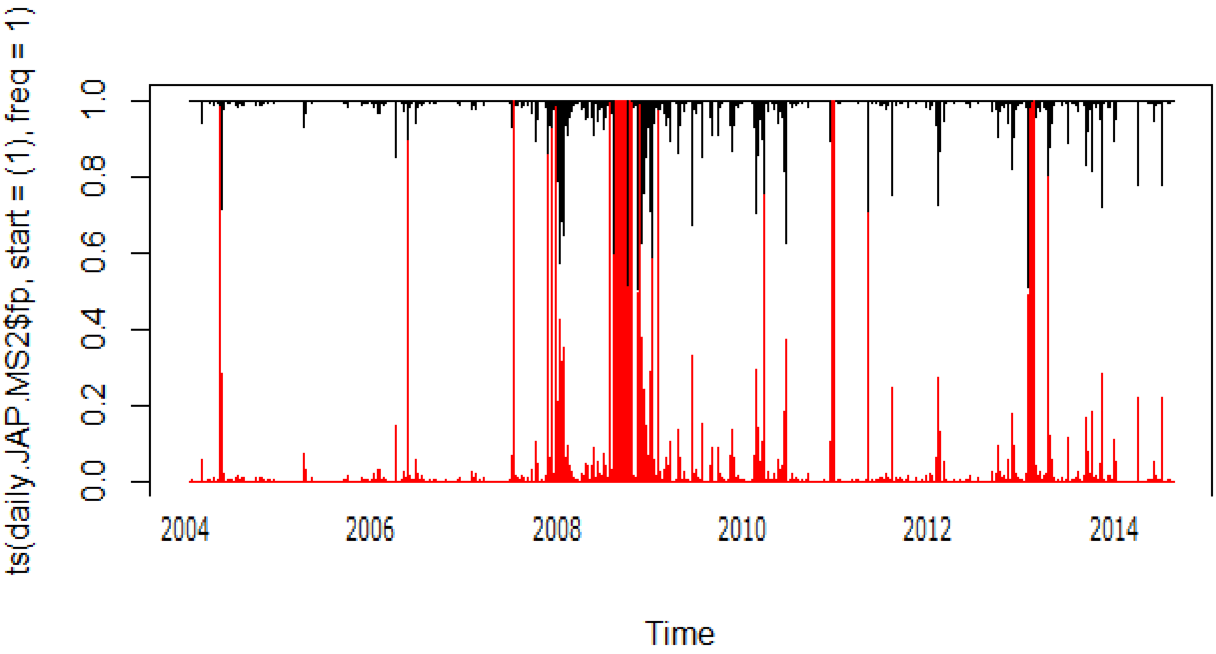
1.7.7 MSBVAR – Daily Frequency HSI: p=5, h=3



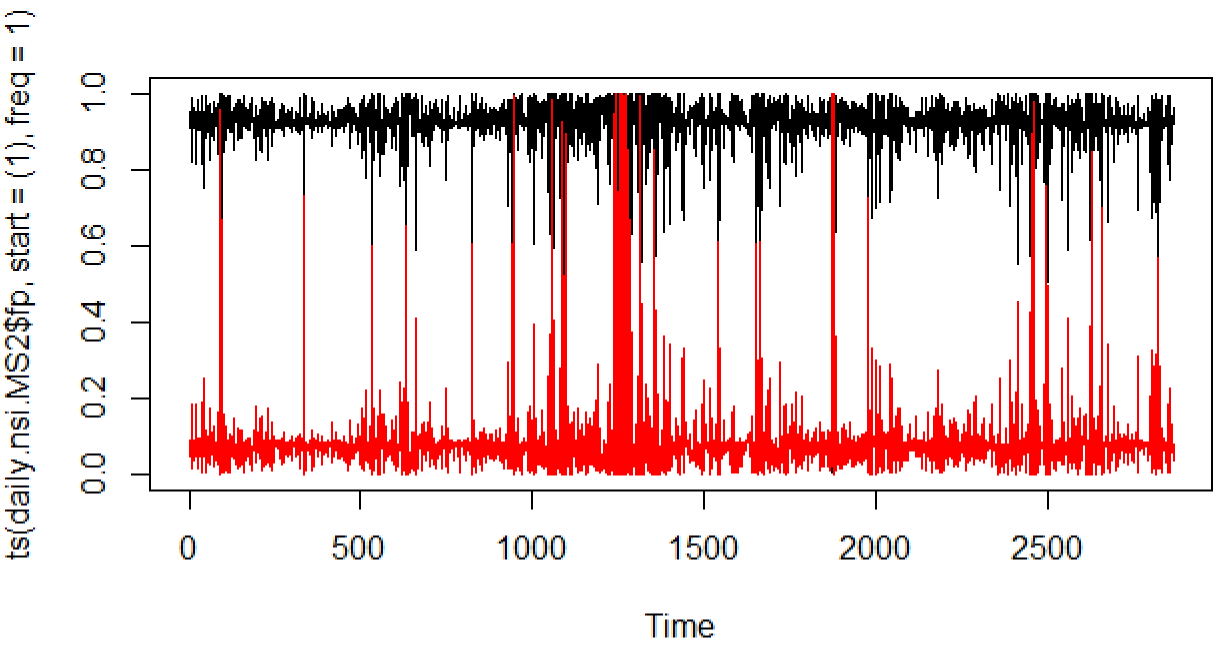
1.7.8 MSBVAR – Daily Frequency HSI: p=10, h=3



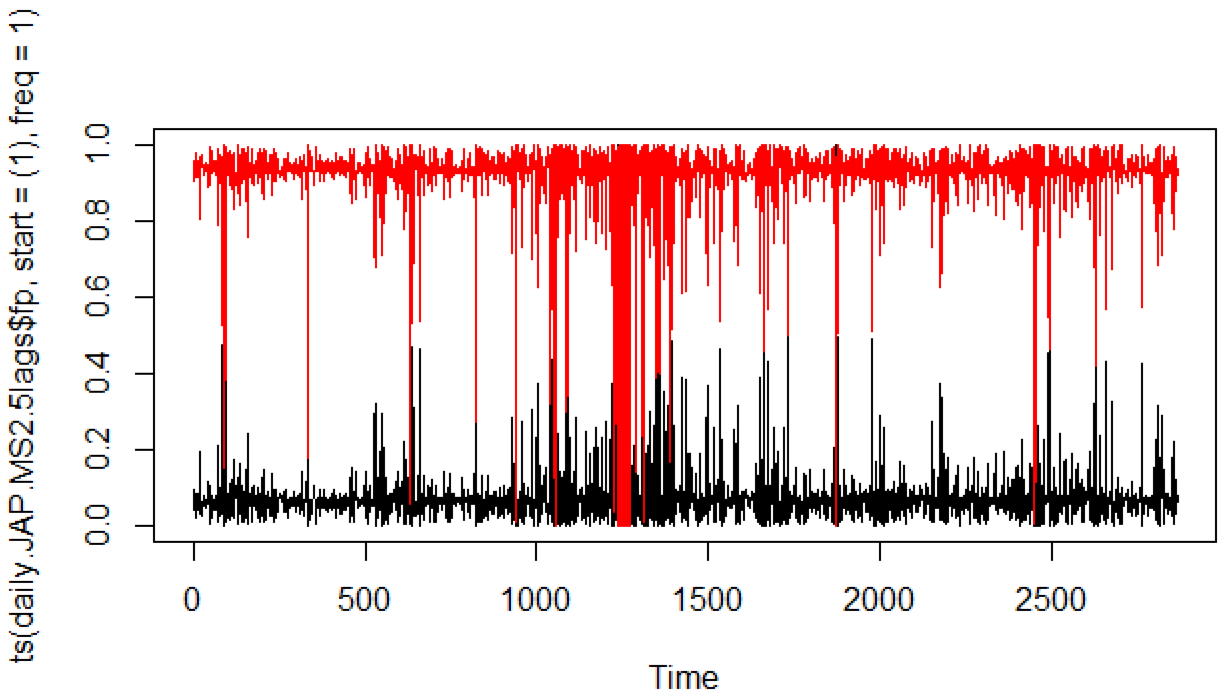
1.7.9 MSBVAR – Daily Frequency NSI: p=1, h=2



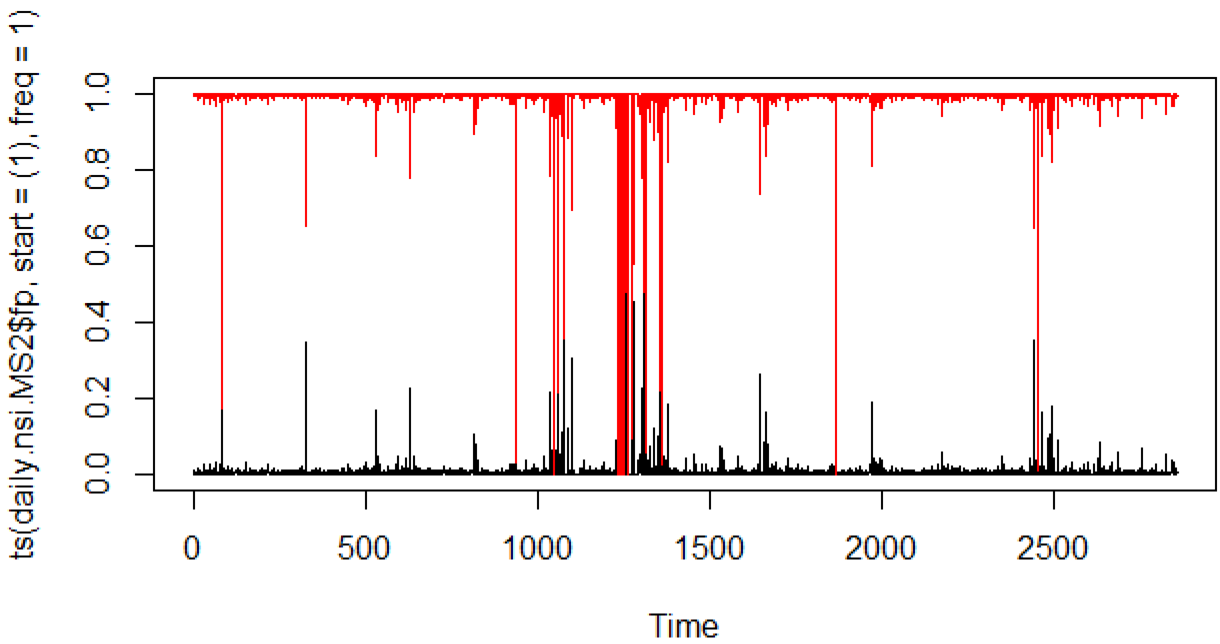
1.7.10 MSBVAR – Daily Frequency NSI: p=2, h=2



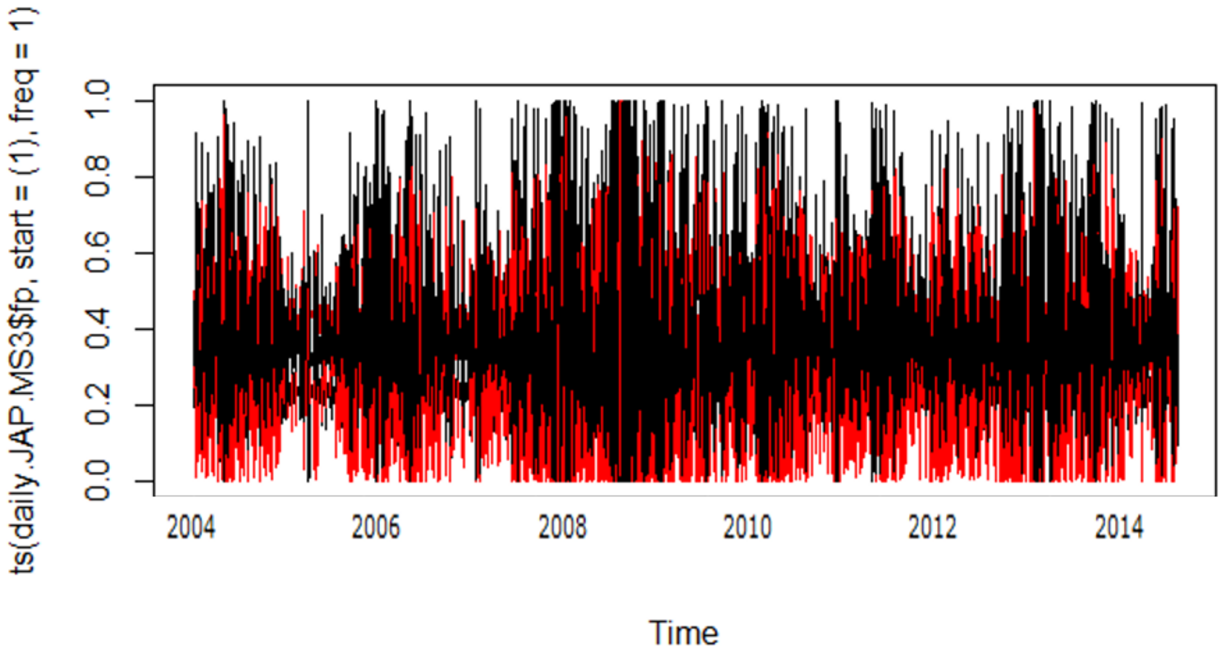
1.7.11 MSBVAR – Daily Frequency NSI: p=5, h=2



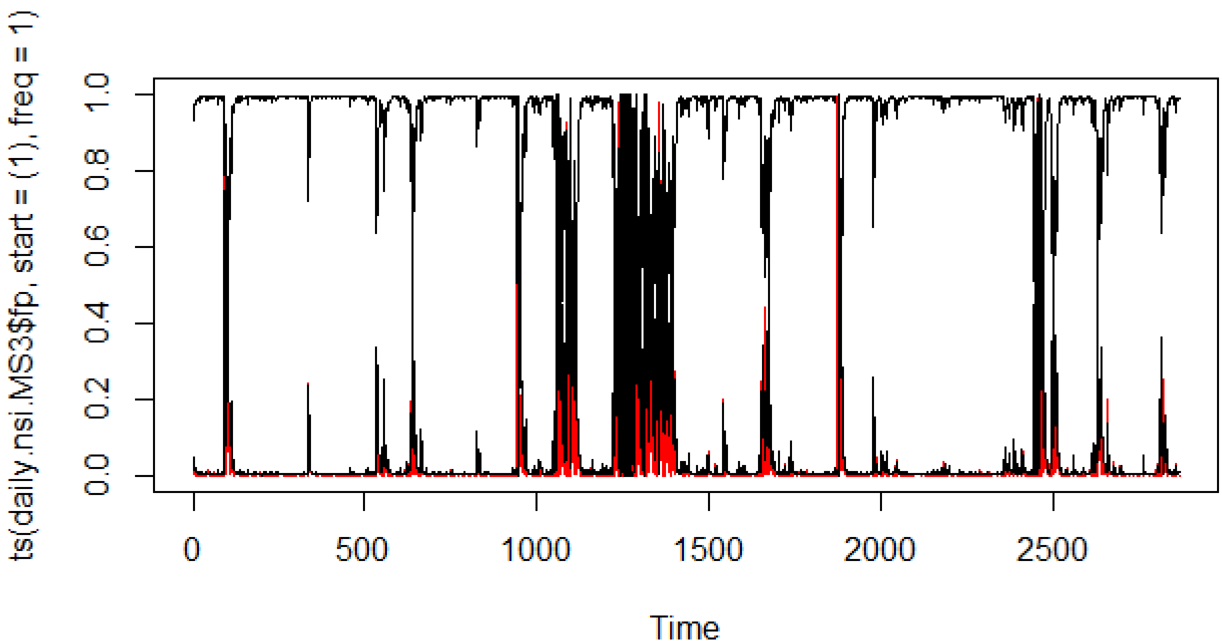
1.7.12 MSBVAR – Daily Frequency NSI: p=10, h=2



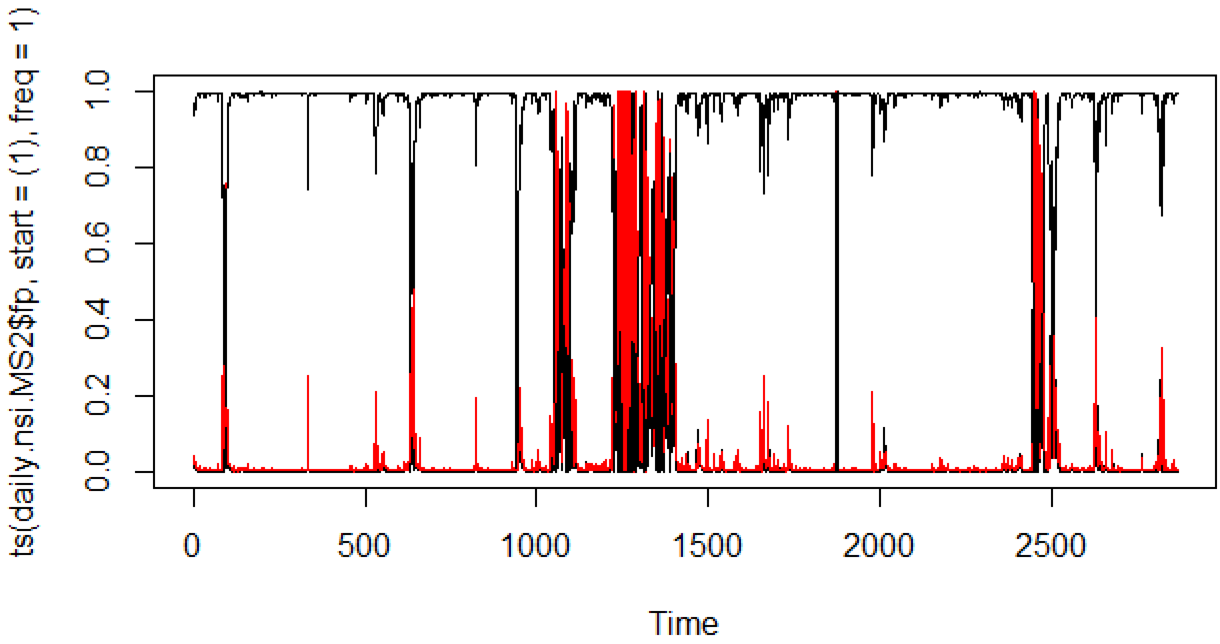
1.7.13 MSBVAR – Daily Frequency NSI: p=1, h=3



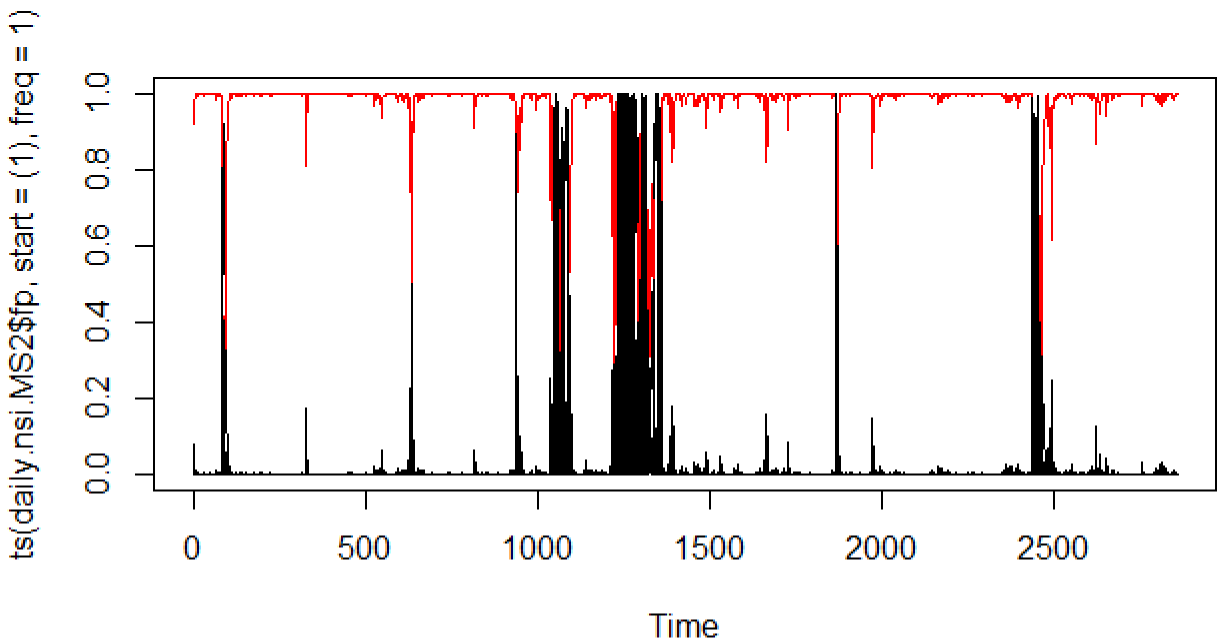
1.7.14 MSBVAR – Daily Frequency NSI: p=2, h=3



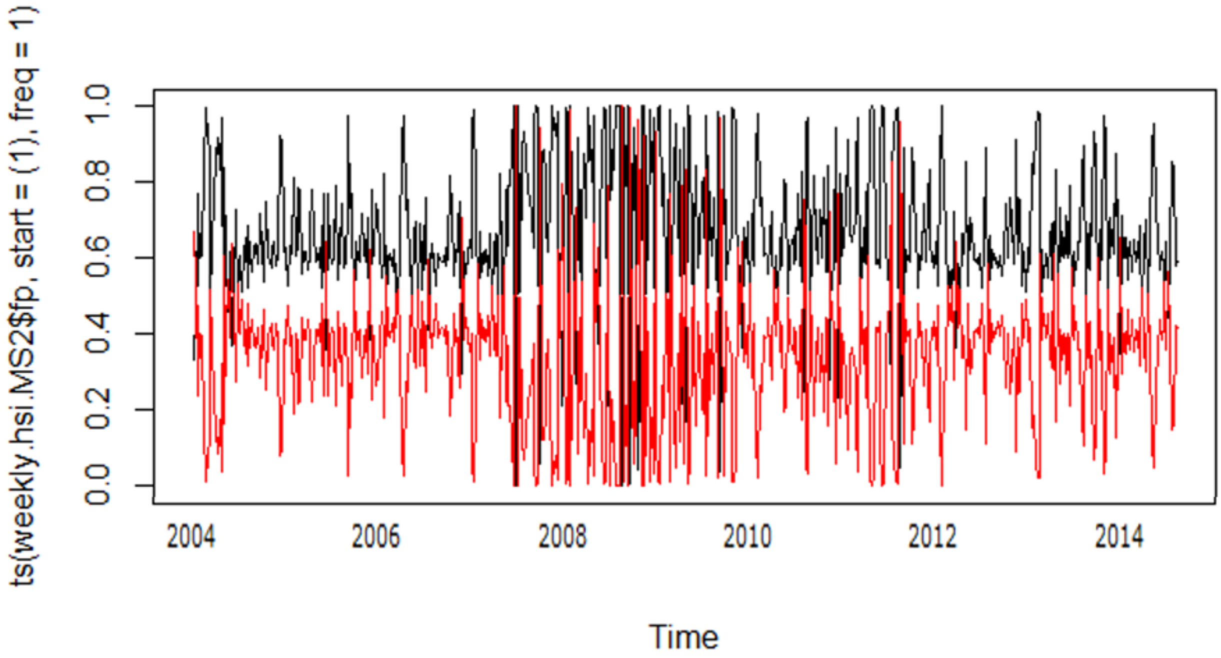
1.7.15 MSBVAR – Daily Frequency NSI: p=5, h=3



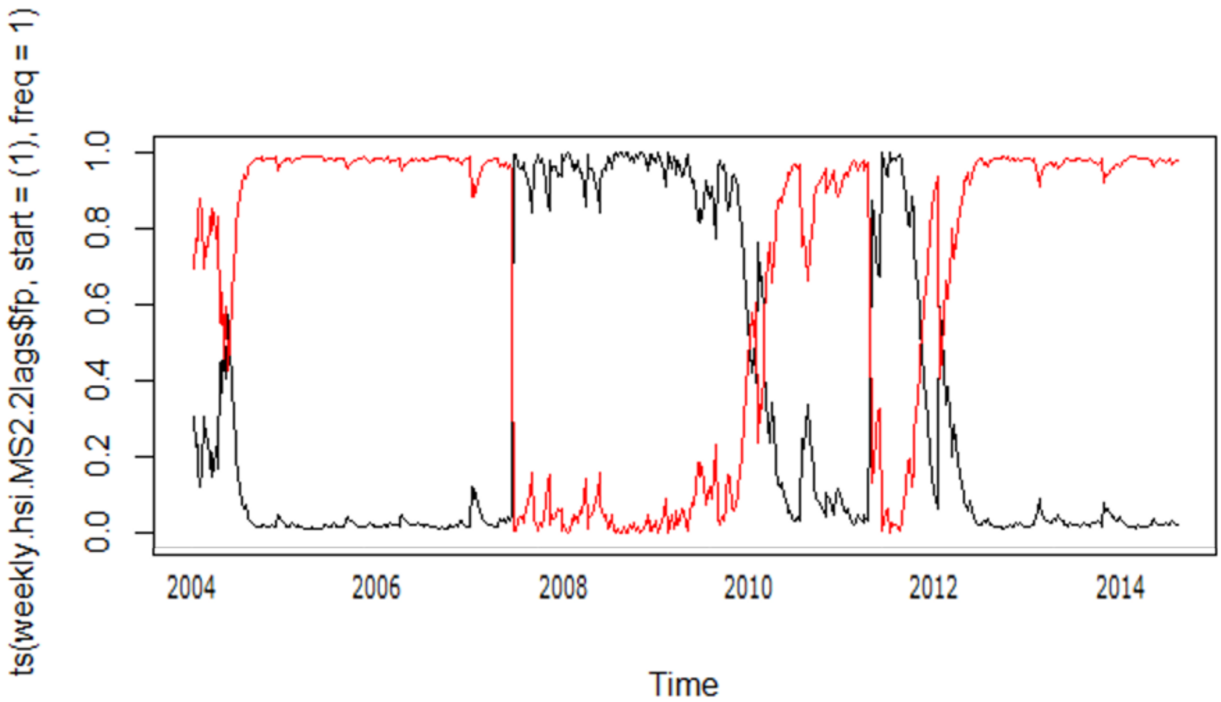
1.7.16 MSBVAR – Daily Frequency NSI: p=10, h=3



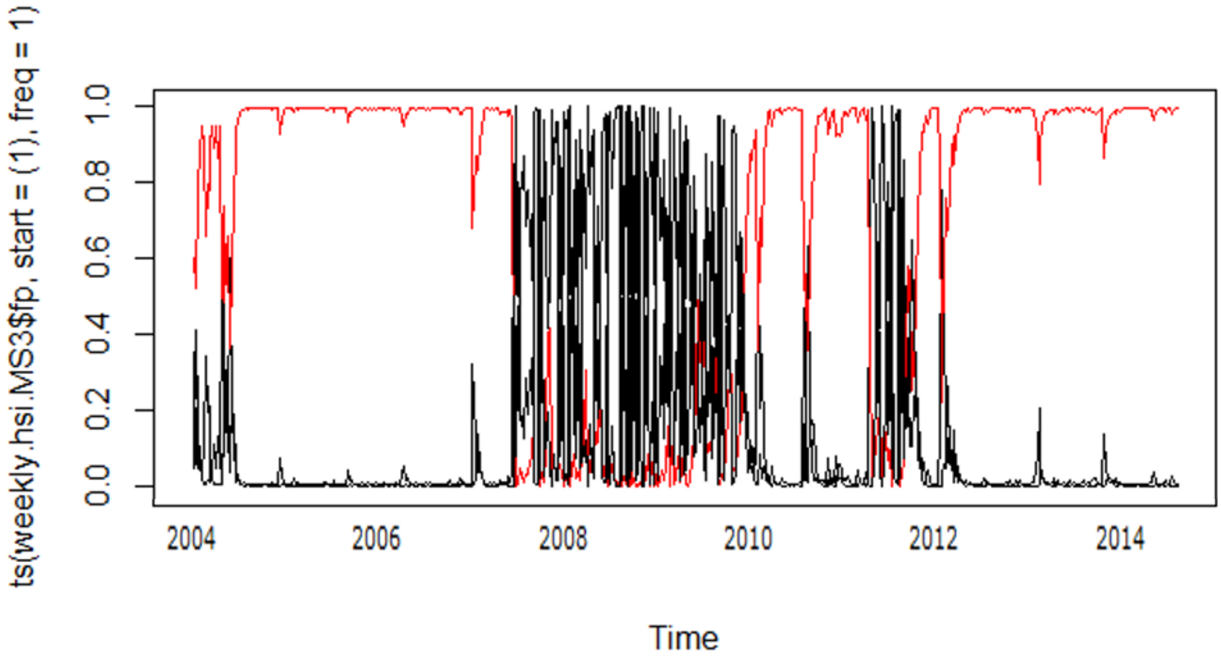
1.7.17 MSBVAR – Weekly Frequency HSI: p=1, h=2



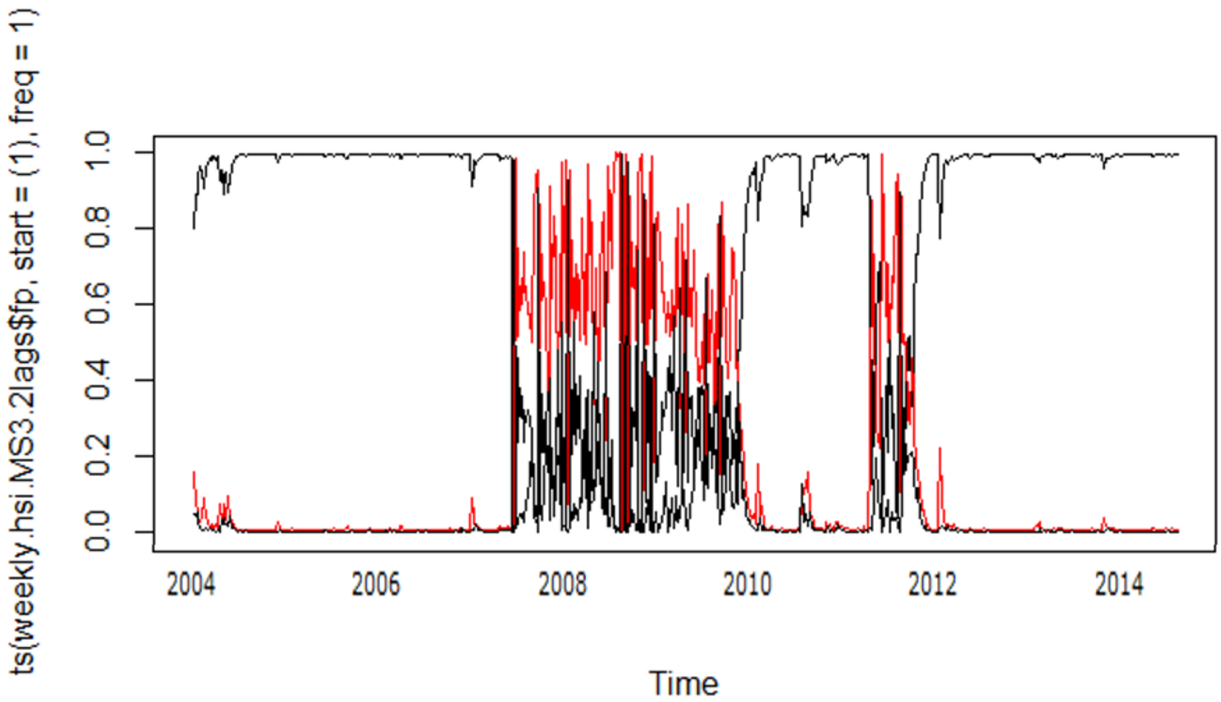
1.7.18 MSBVAR – Weekly Frequency HSI: p=2, h=2



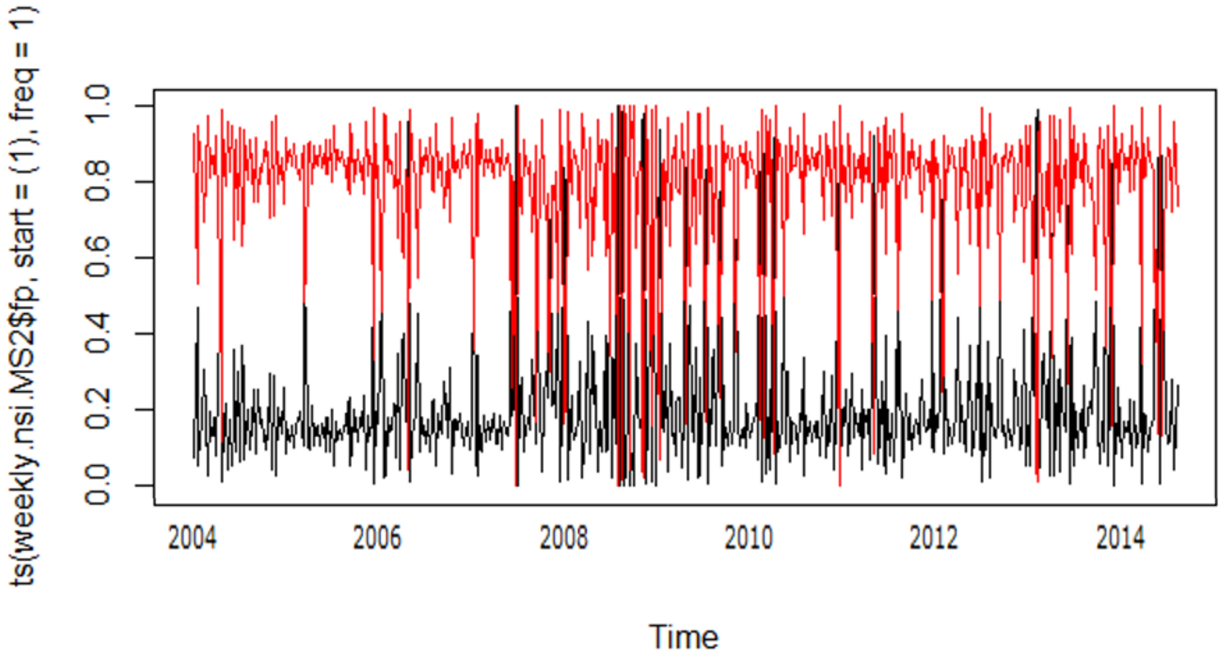
1.7.19 MSBVAR – Weekly Frequency HSI: p=1, h=3



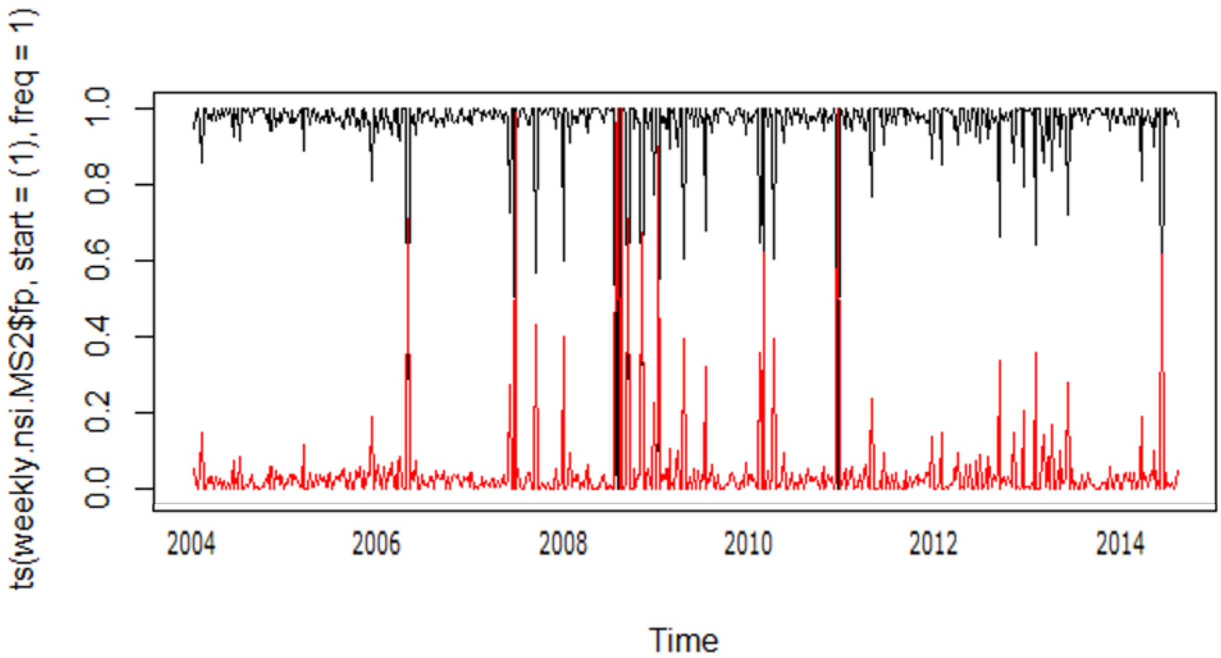
1.7.20 MSBVAR – Weekly Frequency HSI: p=2, h=3



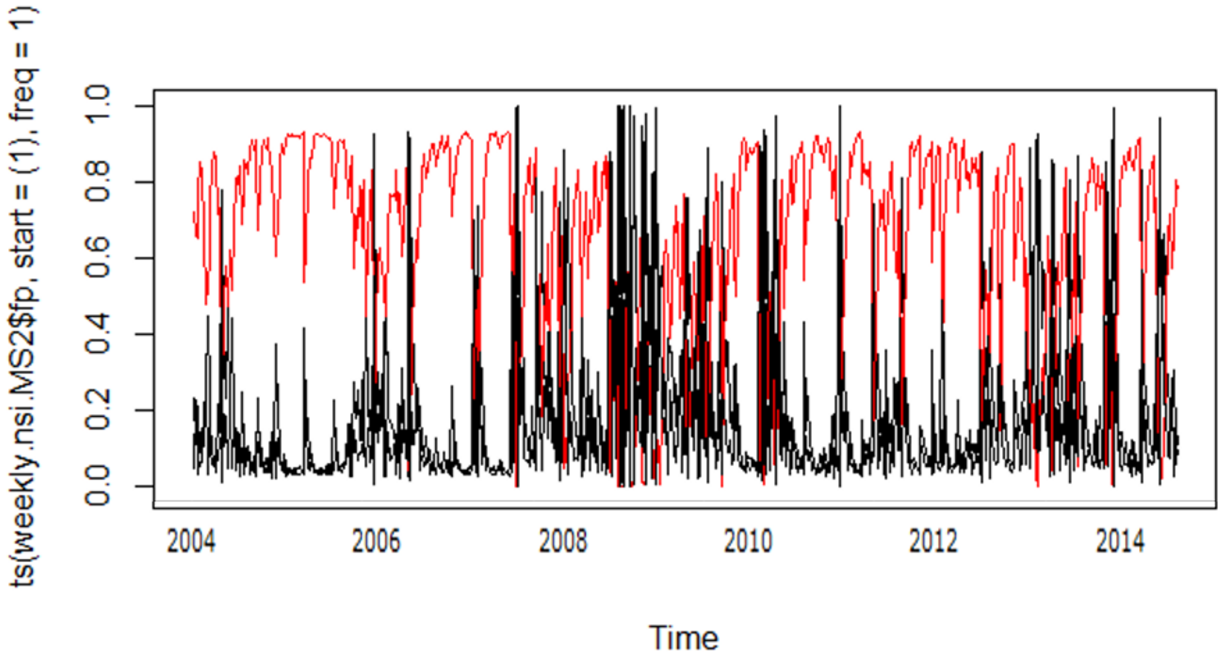
1.7.21 MSBVAR – Weekly Frequency NSI: p=1, h=2



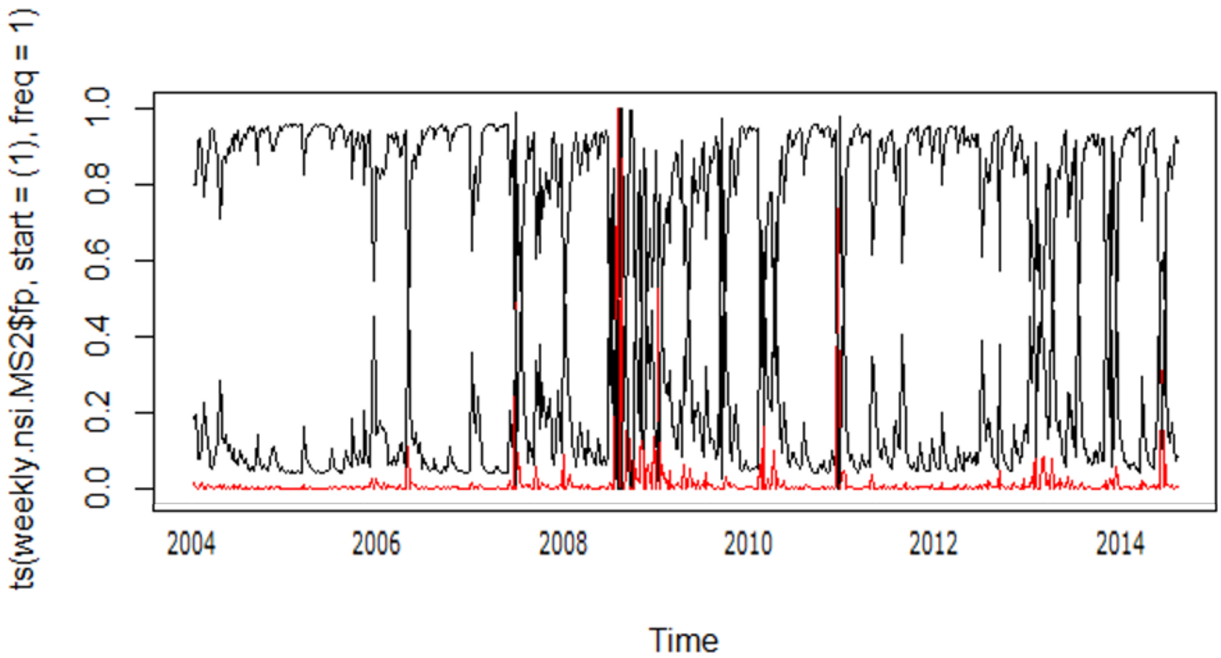
1.7.22 MSBVAR – Weekly Frequency NSI: p=2, h=2



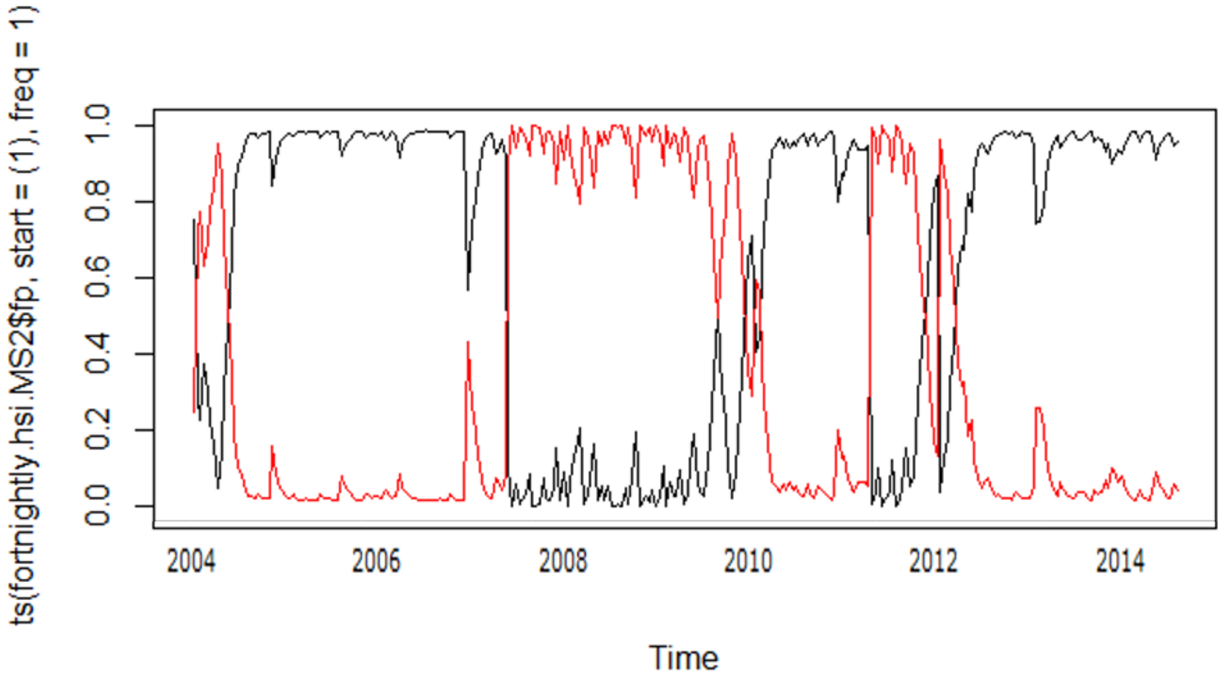
1.7.23 MSBVAR – Weekly Frequency NSI: p=1, h=3



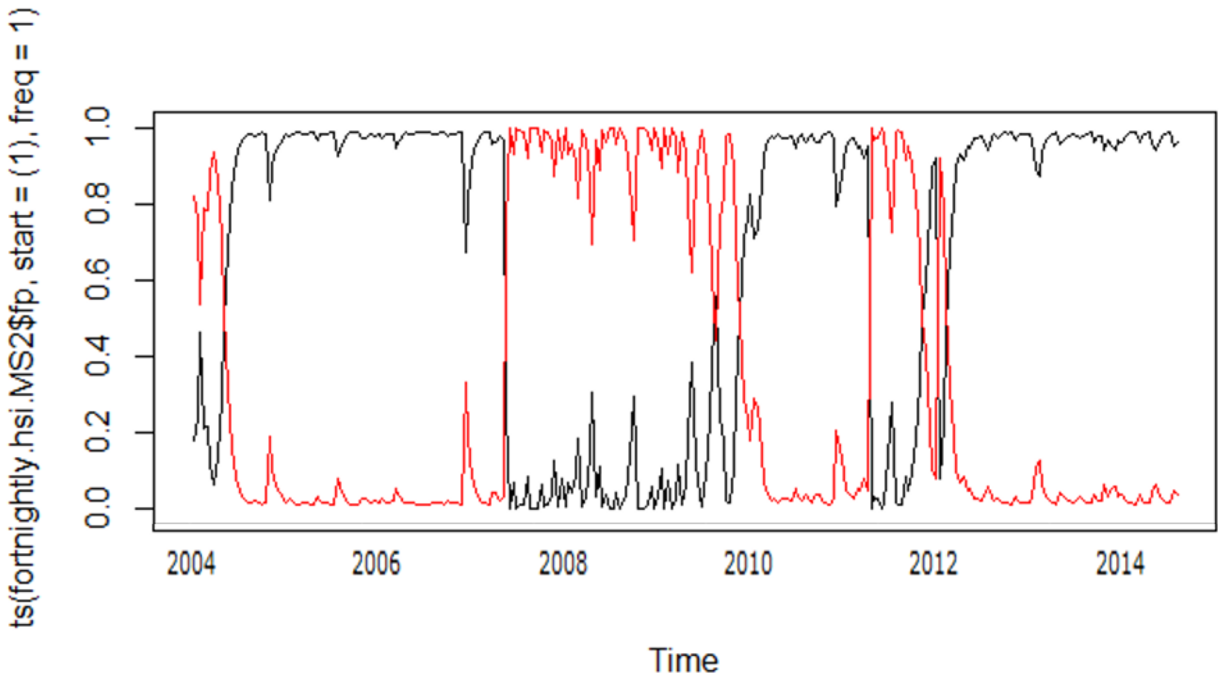
1.7.24 MSBVAR – Weekly Frequency NSI: p=2, h=3



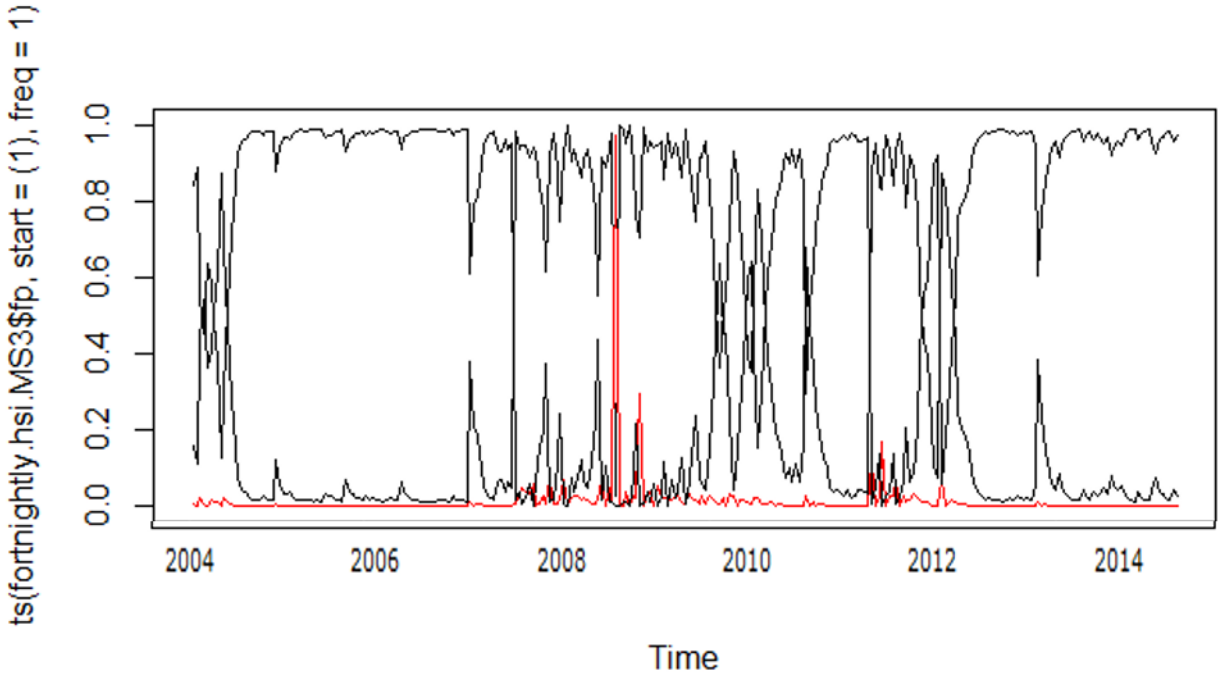
1.7.25 MSBVAR – Fortnightly Frequency HSI: p=1, h=2



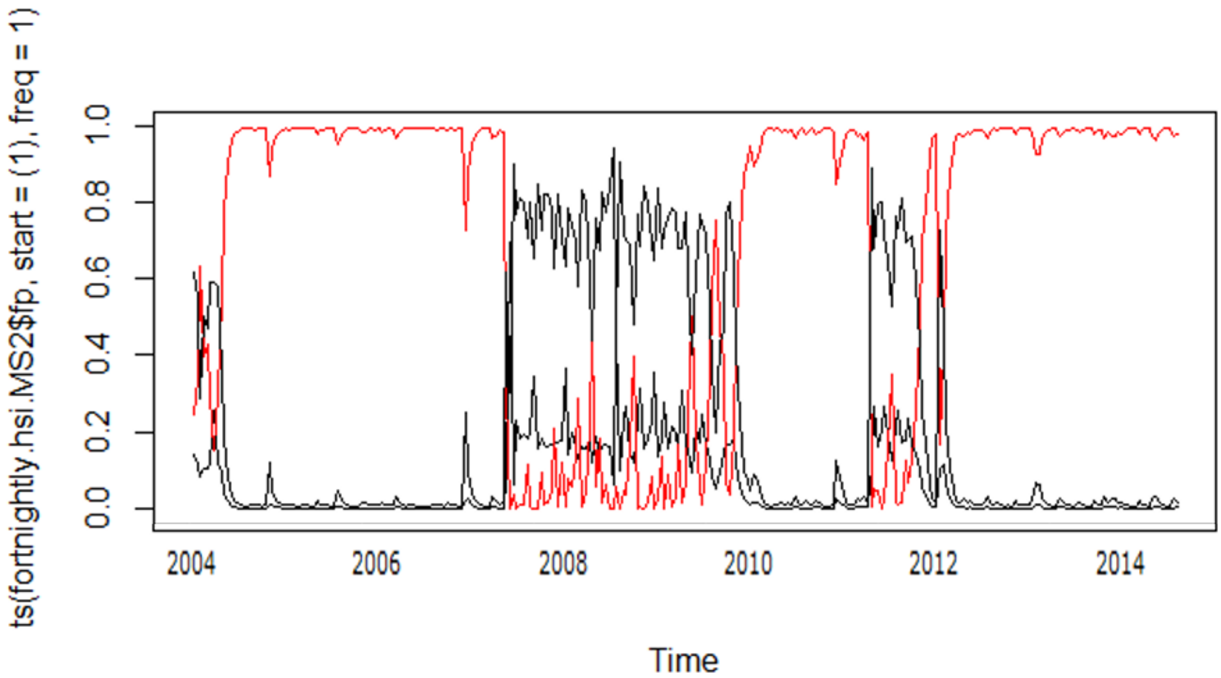
1.7.26 MSBVAR – Fortnightly Frequency HSI: p=2, h=2



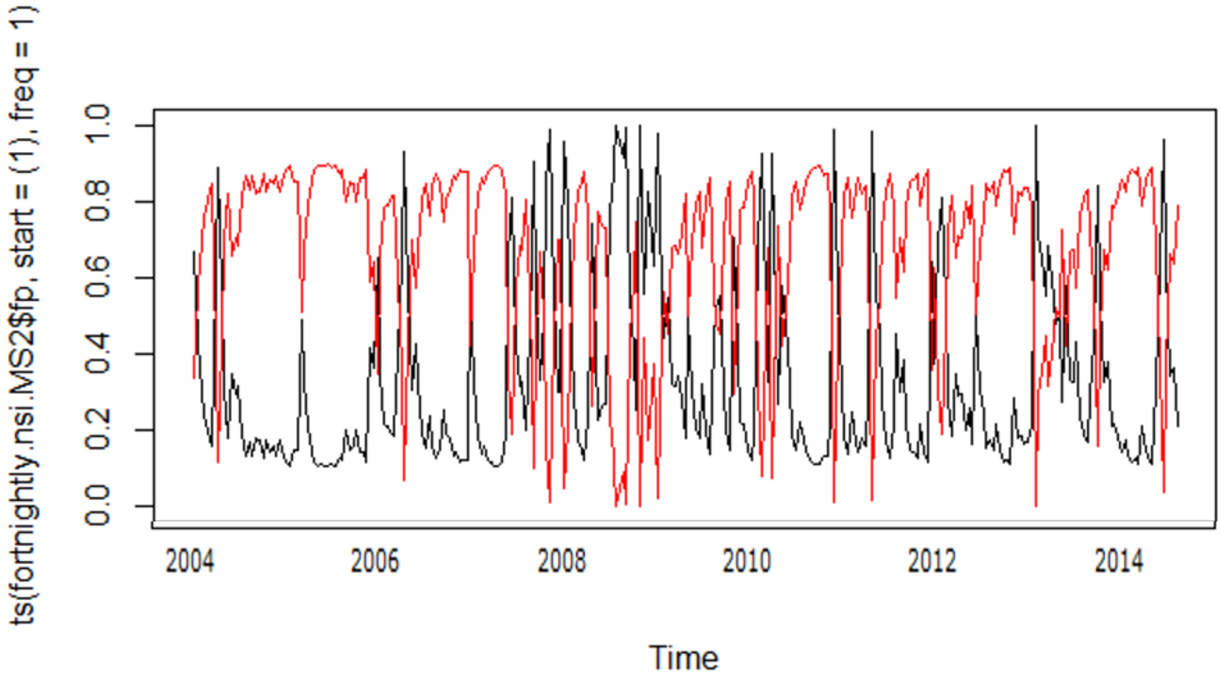
1.7.27 MSBVAR – Fortnightly Frequency HSI: p=1, h=3



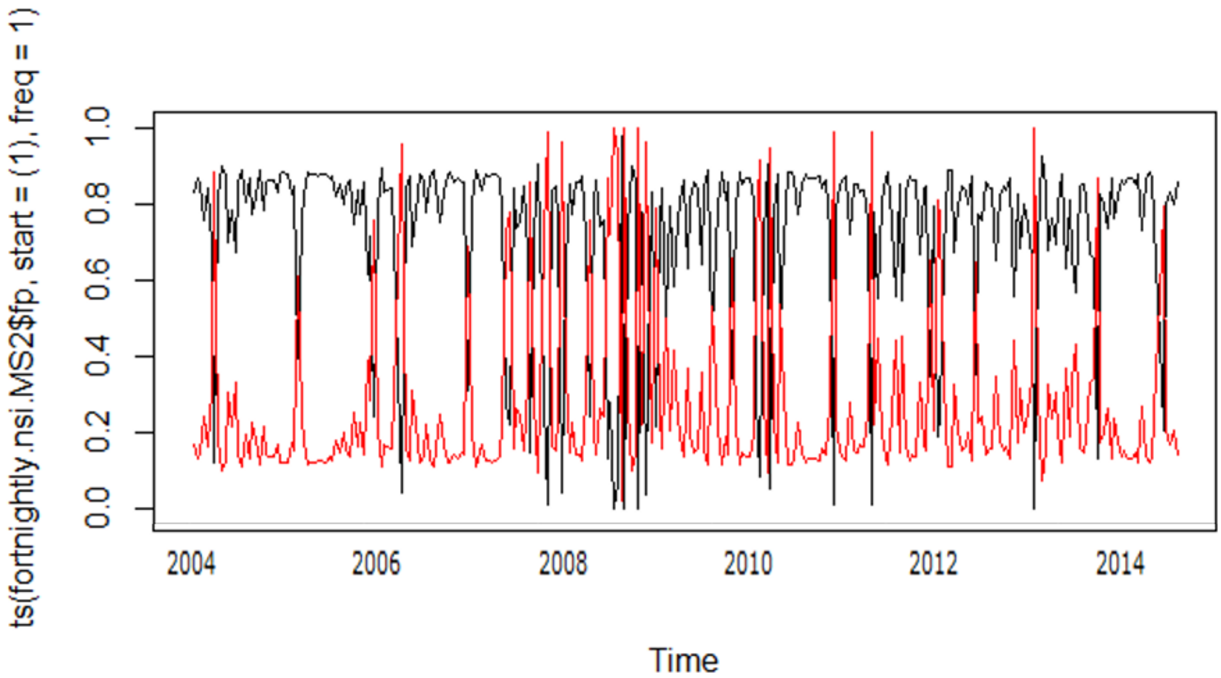
1.7.28 MSBVAR – Fortnightly Frequency HSI: p=2, h=3



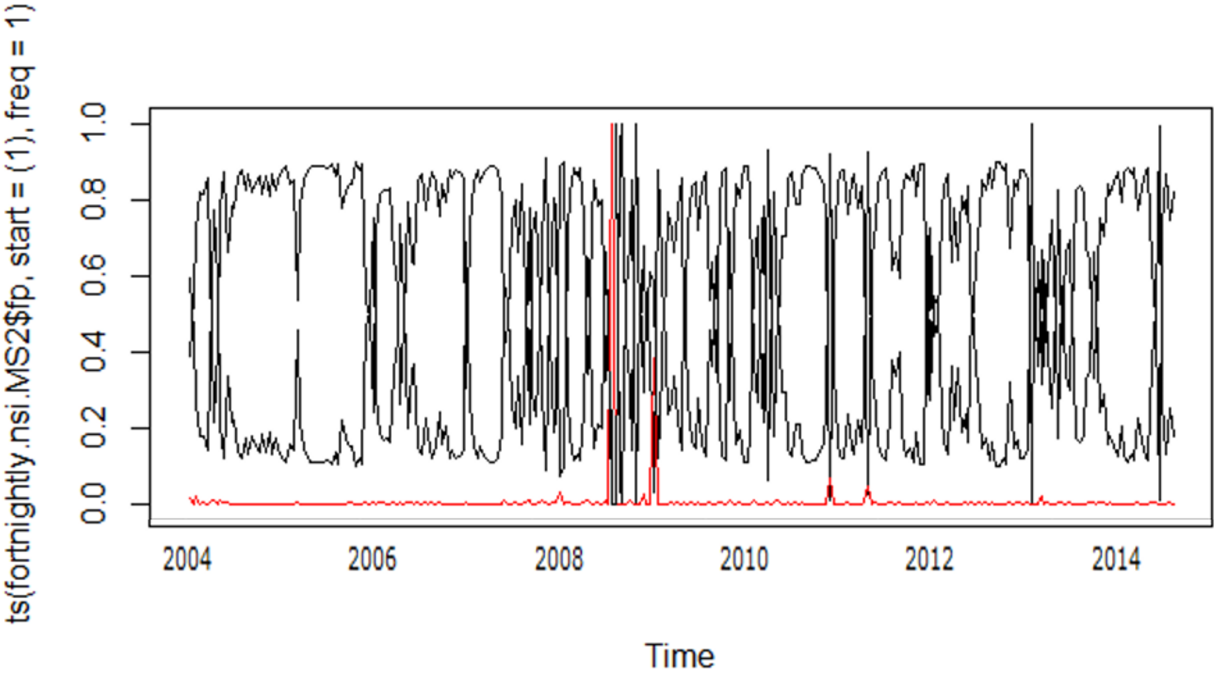
1.7.29 MSBVAR – Fortnightly Frequency NSI: p=1, h=2



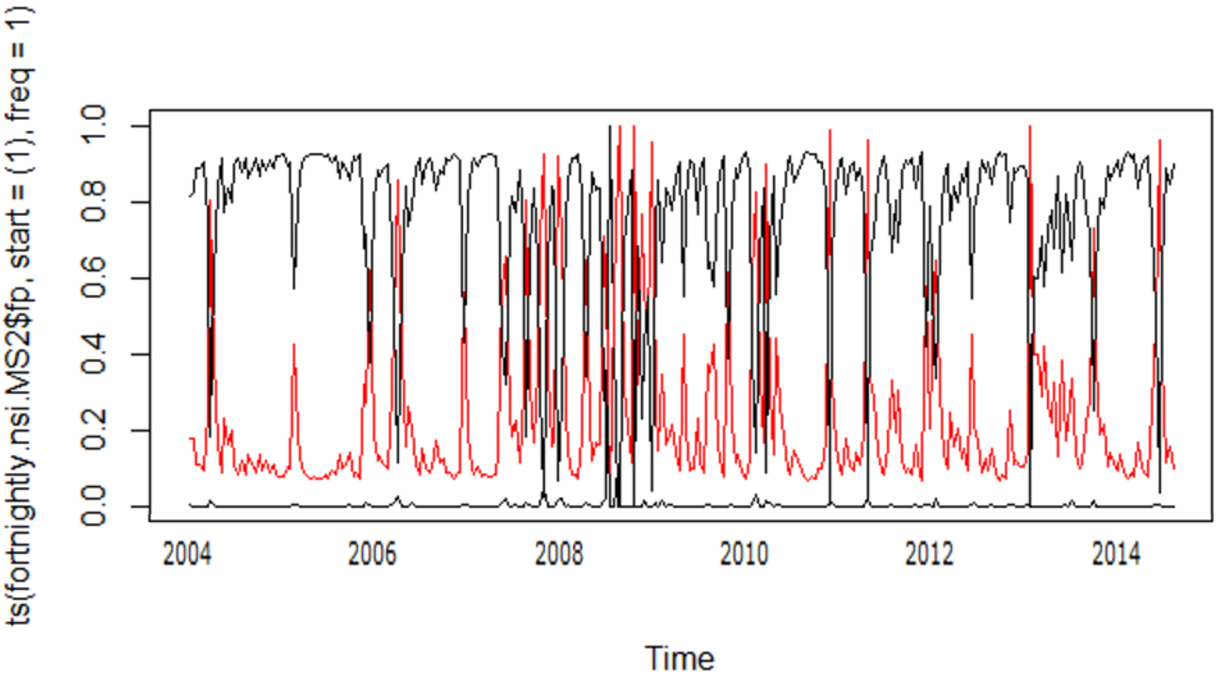
1.7.30 MSBVAR – Fortnightly Frequency NSI: p=2, h=2



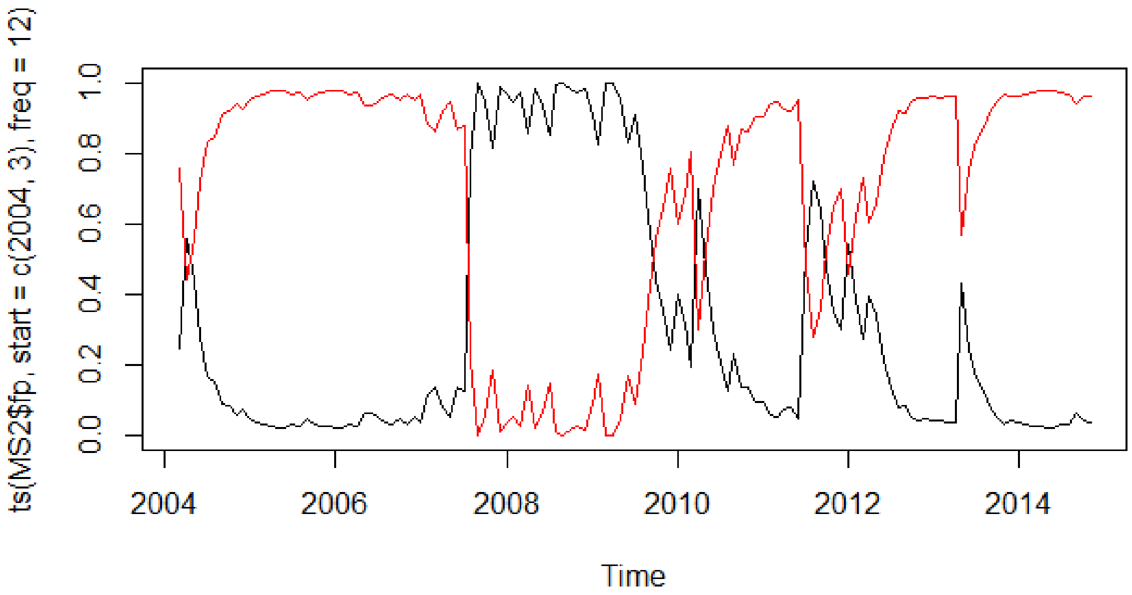
1.7.31 MSBVAR – Fortnightly Frequency NSI: p=1, h=3



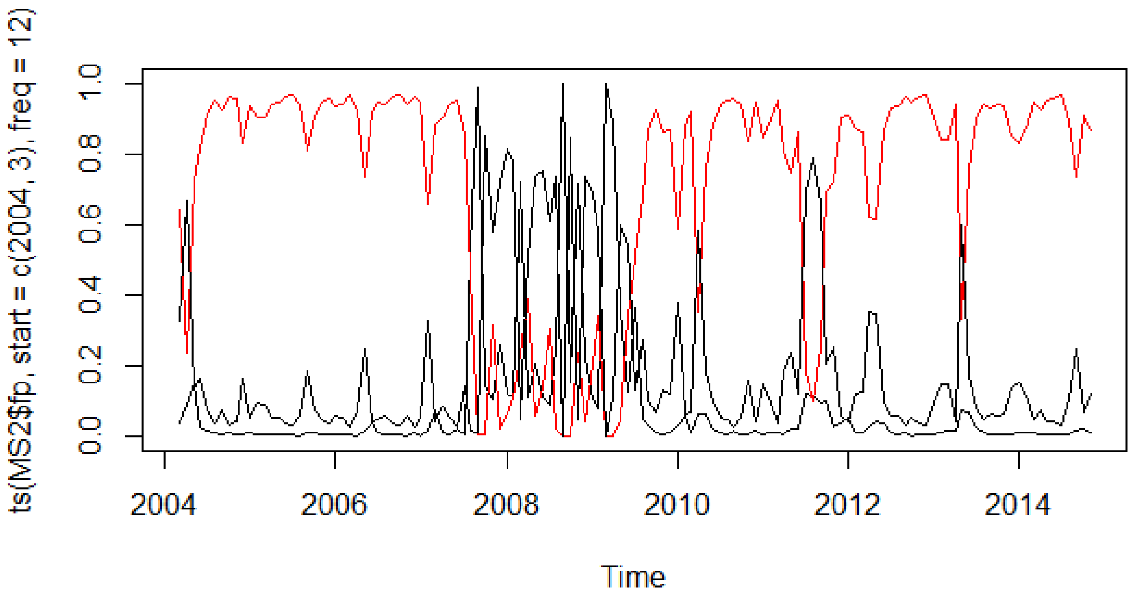
1.7.32 MSBVAR – Fortnightly Frequency NSI: p=2, h=3



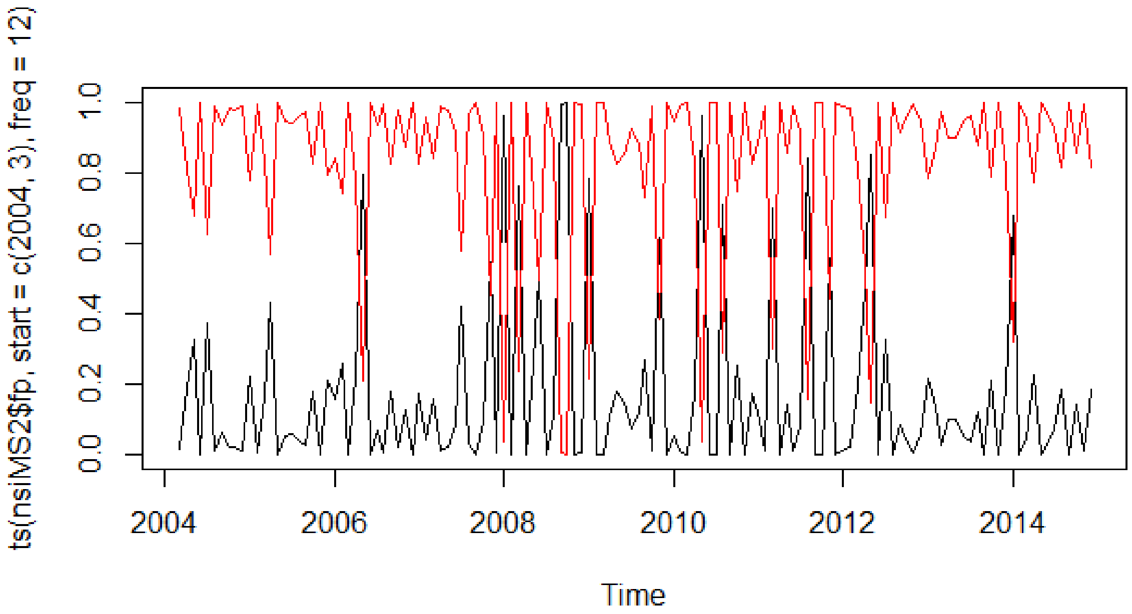
1.7.33 MSBVAR – Monthly Frequency HSI: p=1, h=2



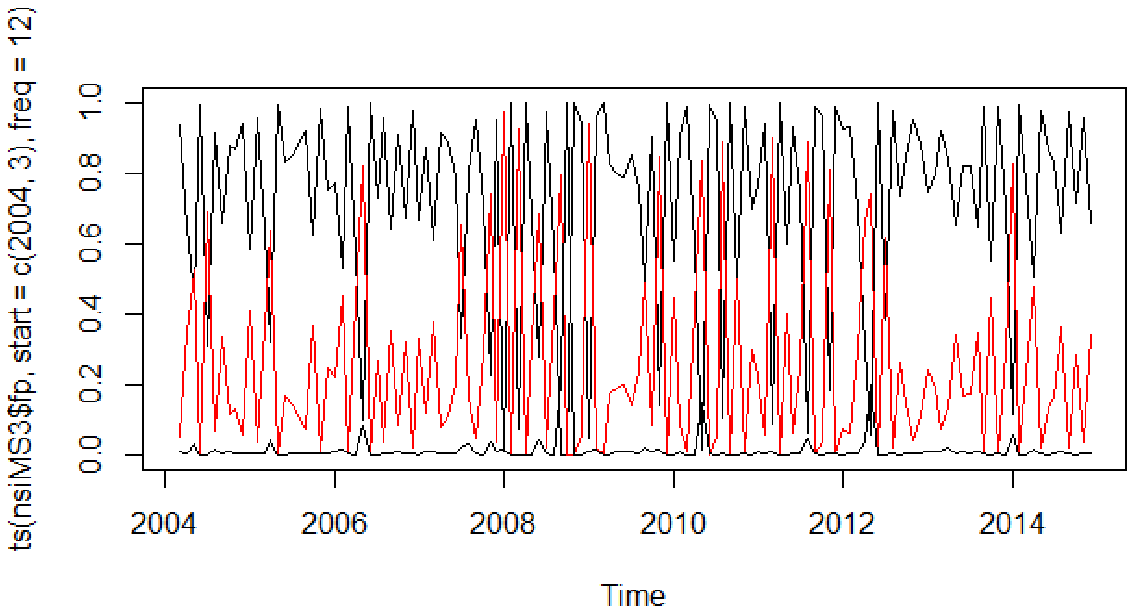
1.7.34 MSBVAR – Monthly Frequency HSI: p=1, h=3



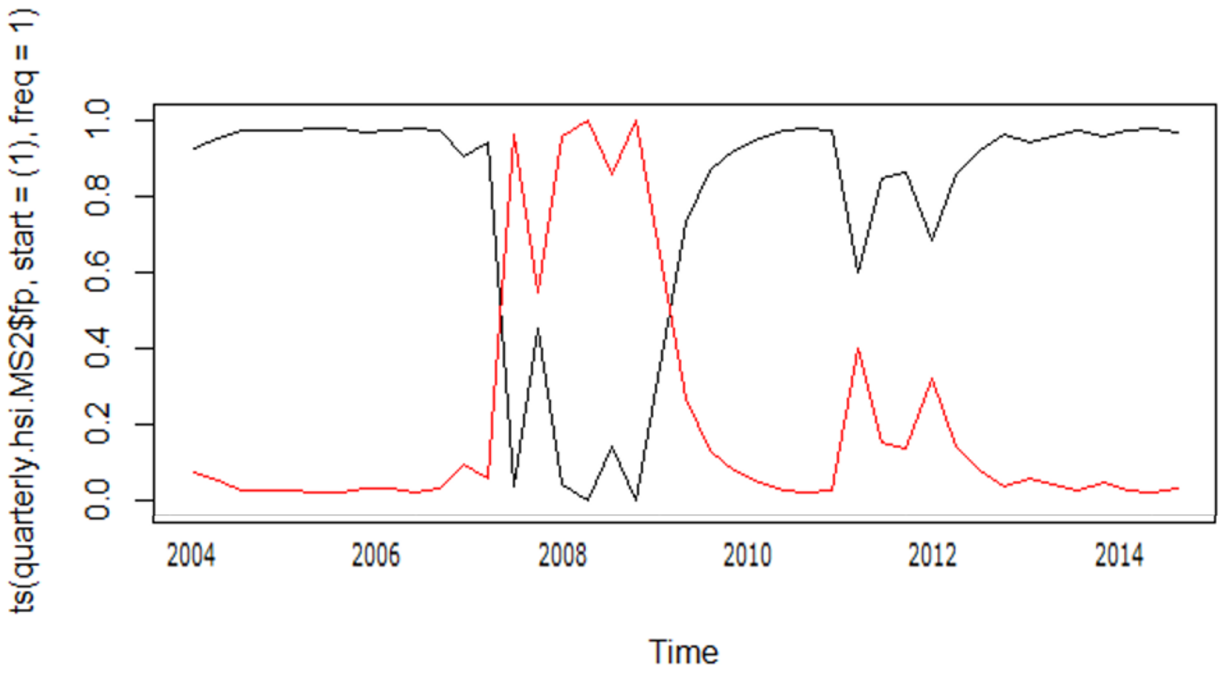
1.7.35 MSBVAR – Monthly Frequency NSI: p=1, h=2



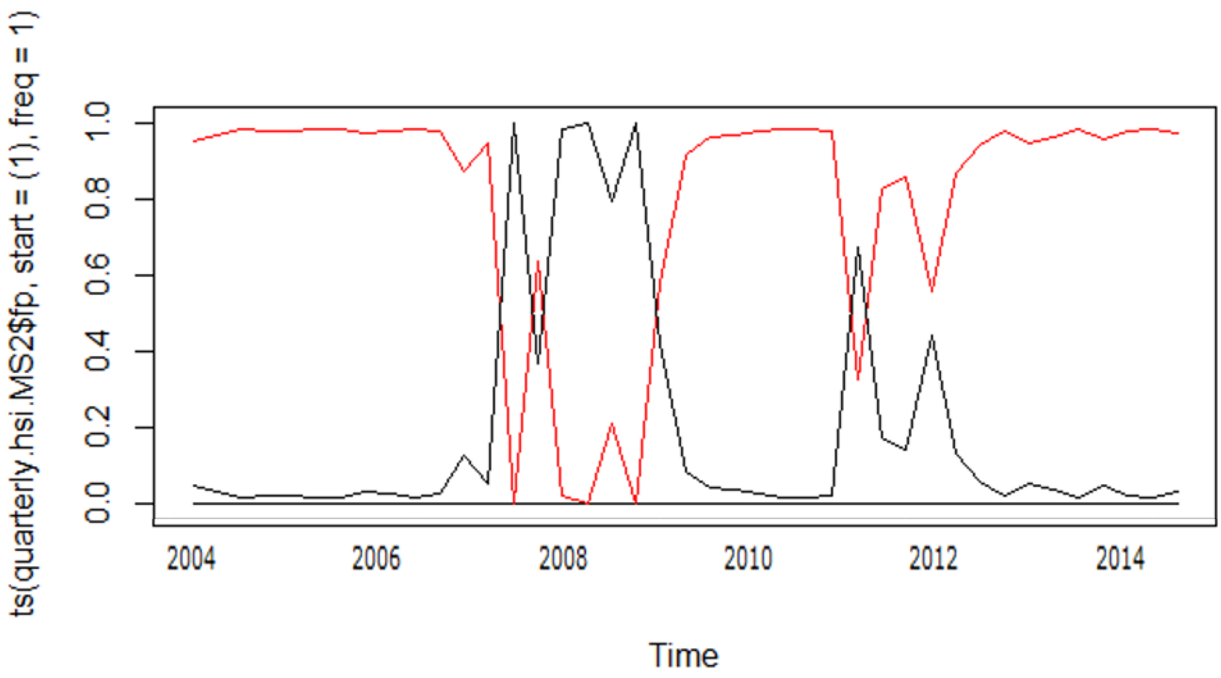
1.7.36 MSBVAR – Monthly Frequency NSI: p=1, h=3



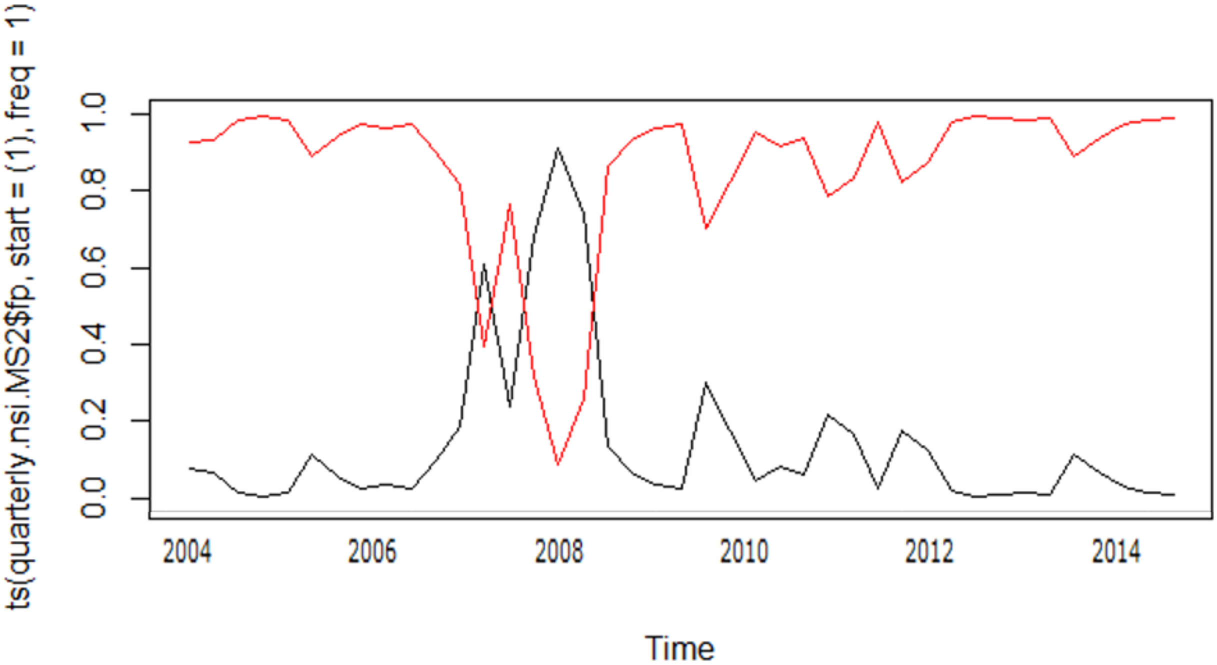
1.7.37 MSBVAR – Quarterly Frequency HSI: p=1, h=2



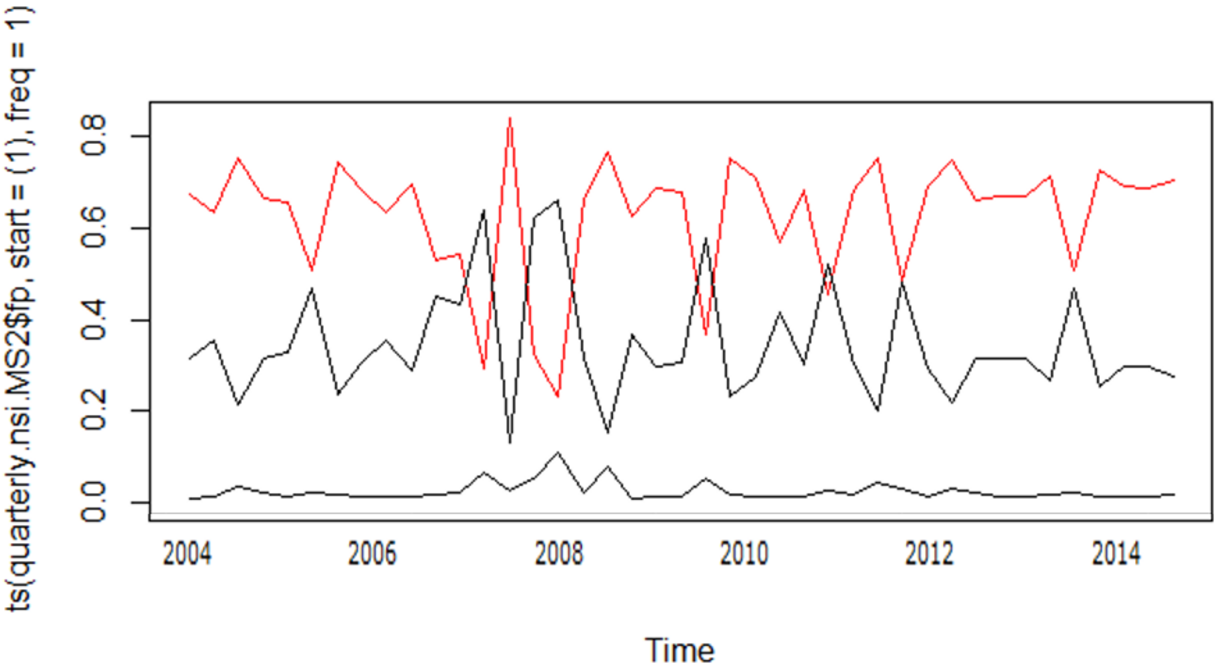
1.7.38 MSBVAR – Quarterly Frequency HSI: p=1, h=3



1.7.39 MSBVAR – Quarterly Frequency HSI: p=1, h=2



1.7.40 MSBVAR – Quarterly Frequency HSI: p=1, h=3



1.8 Summaries of Correlation Results by Data Frequency

1.8.1 Correlation Results – Weighted Pearson Coefficients

Frequency	Total	Tranquil	Crisis	% Change
Daily	0.584361	0.515000	0.709219	137.71%
Weekly	0.655699	0.558683	0.778254	139.30%
Fortnightly	0.634396	0.242113	0.690367	285.14%
Monthly	0.530019	0.232500	0.816354	351.12%
Quarterly	0.096610	0.222710	-0.314540	-141.23%

1.8.2 Correlation Results – Weighted Spearman Coefficients

Frequency	Total	Tranquil	Crisis	% Change
Daily	0.502596	0.488897	0.648043	132.55%
Weekly	0.563454	0.511813	0.645791	126.18%
Fortnightly	0.530204	0.162764	0.652477	400.87%
Monthly	0.361159	0.183372	0.794872	433.48%
Quarterly	0.074902	0.203785	-0.457360	-224.43%